

THE UNIVERSITY OF HULL

Quantification of Training Load, Neuromuscular Fatigue, Biochemical and
Endocrine Responses to Fast Bowling in Cricket

being a Thesis submitted for the Degree of Doctor of Philosophy

at the University of Hull

by

James William Bray, MSc, BSc (Hons.)

June 2017

Table of Contents	
List of Figures and Tables	3
Acknowledgements	9
List of Published Works	10
List of Abbreviations	11
Abstract	16
1. General Introduction	18
1.1. Aims	26
2. Literature Review	27
2.1. The Physiological Requirements of Fast Bowling	27
2.2. Methods of Quantifying Training Load	31
2.2.1. Overview of Training Load	32
2.2.2 Time-Motion Analysis (TMA)	35
2.2.3. Global Positioning Systems (GPS)	37
2.2.4. Validity and Reliability of GPS	43
2.2.5. Accelerometry	48
2.3. Overview of Neuromuscular Fatigue (NMF)	57
2.3.1. Neuromuscular Fatigue in Team Sports	60
2.3.2. Neuromuscular Fatigue within Fast Bowling	72
2.3.3. Validity and Reliability of Countermovement Jump (CMJ) Protocols	75
2.4. Biochemical Markers of Fatigue	76
2.4.1 Creatine Kinase (CK)	78
2.4.2. Uric Acid (UA) and Urea	89
2.4.3. Salivary Cortisol (sCort.)	91
2.4.4. Validity and Reliability of Biochemical Markers of Fatigue	99
2.5. Summary	101
3. General Methodologies	103
4. A Descriptive Analysis of Fast Bowling Workload and Playing Schedule in a Domestic Professional Cricket Season	117
4.1. Introduction	117
4.2. Methods	122
4.3. Results	124
4.4. Discussion	137

5. Using Microtechnology to Evaluate the Between- and Within-Match Variability of Professional Twenty20 Cricket Fast Bowlers	143
5.1. Introduction	143
5.2. Methods	147
5.3. Results.....	152
5.4. Discussion	157
6. Neuromuscular Fatigue Responses During a Professional Cricket Season..	162
6.1. Introduction	162
6.2. Methods	166
6.3. Results.....	172
6.4. Discussion	184
7. Short-term Neuromuscular Fatigue and the Biochemical and Endocrine Responses Associated with an Indoor Bowling Simulation.....	191
7.1. Introduction	191
7.2. Methods	198
7.3. Results.....	207
7.4. Discussion	231
8. General Discussion, Conclusions, Limitations, Future Research Recommendations and Practical Applications	238
8.1. General Discussion	239
8.2. Conclusions	248
8.3. Limitations	249
8.4. Future Research Recommendations	252
8.5. Practical Applications	254
9. References	257
10. Appendices.....	288

List of Figures and Tables

Chapter 1. Introduction

- Figure 1.1. A schematic of the fast bowling action. Adapted from ...22
Olivier et al. (2016).

Chapter 2. Literature Review

- Figure 2.1. The energy demands of different cricketing activities ...28
compared to other sports and activities. Adapted from
Fletcher (1955), Christie (2012) and Noakes and Durandt
(2000).
- Figure 2.2. Comparison of aerobic physiological characteristics ...29
between South African international cricket and rugby
players. Adapted from Noakes and Durandt (2000).
- Figure 2.3. Comparison of anaerobic physiological characteristics ...30
between South African international cricket and rugby
players. Adapted from Noakes and Durandt (2000).
- Table 2.1. Summary of early cricket-based time-motion analysis ...36-
research. 37
- Figure 2.4. PlayerLoad™ equation. Adapted from Boyd, Ball, and ...49
Aughey (2011).

Chapter 3. General Methodologies

- Figure 3.1. Portable MEMS device (L) and fast bowler wearing a ...105
bespoke neoprene vest (R). The arrow indicates unit
placement, between the scapulae within a custom-made
pouch as part of the bespoke neoprene vest.

Table 3.1.	Movement Category Speeds, as reported by Petersen, Portus, and Dawson (2009); Petersen, Pyne, Portus, and Dawson (2009), and Petersen, Pyne, Dawson, Portus, and Kellett (2010).	...106
Figure 3.2.	Screen-shot of Sprint software to highlight the cropping process. Arrow (L) indicates the raw accelerometer trace, with arrow (R) indicating the GPS map.	...109
Figure 3.3.	Cricket Australia-Australian Institute of Sport (CA-AIS) fast bowling skills test set-up. Adapted from Duffield, Carney, and Karppinen (2009) and M. Portus, Timms, Spratford, Morrison, and Crowther (2010).	...111- 112

Chapter 4. A Descriptive Analysis of Fast Bowling Competition Load and Playing Schedule in a Domestic Professional Cricket Season

Table 4.1.	Extrinsic fast bowling competition load variables for bowlers participating in the 2011 Season.	...125
Table 4.2.	Descriptive statistics for the extrinsic fast bowling competition load variables for each individual competition format (mean \pm <i>SD</i>).	...127- 128
Table 4.3.	Descriptive statistics for frequency of match exposure for each individual competition format (mean \pm <i>SD</i>).	...130
Figure 4.1.	Comparison of overs bowled across the entire season between bowler classifications. *Denotes a significant difference in overs bowled compared to support bowlers ($P \leq 0.05$). **Denotes a significant difference in overs	...131

bowled compared to support bowlers ($P \leq 0.01$). Data presented as mean \pm *SD*.

Figure 4.2.	Comparison of deliveries bowled across the entire season between bowler classifications. **A significant difference in number of deliveries bowled compared to support bowlers ($P \leq 0.01$). Data presented as mean \pm <i>SD</i>132
Table 4.4.	Monthly descriptive statistics of overs and deliveries bowled for each month of competition across the three different competition formats (mean \pm <i>SD</i>).	...133-134
Figure 4.3.	Comparison of cumulative overs bowled for the 28-week regular season between bowler classifications. *A significant difference in number of overs bowled between O-B and S-B ($P \leq 0.05$). Data presented as mean \pm <i>SD</i>136

Chapter 5. Using Microtechnology to Evaluate the Between- and Within-Match Variability of Professional Twenty20 Cricket Fast Bowlers

Table 5.1.	Descriptive fast bowlers ($n = 8$) external training load data (mean \pm <i>SD</i>).	...153
Table 5.2.	Between-match variation of external training load measures.	...154-155
Table 5.3.	Within-match between-over variation (overs 2, 3 & 4, respectively) of external training load measures.	...156

Chapter 6. Neuromuscular Fatigue Responses During a Professional Cricket Season

Figure 6.1.	Flight time (ms) for countermovement jump as a result of bowling time. *A significant difference from pre ($P \leq 0.05$). Data presented as mean \pm SD.	...173
Figure 6.2.	Flight time (ms) for countermovement jump as a result of bowling workload. * A significant difference from LOW to MODERATE ($P \leq 0.05$). ** A significant difference from LOW to HIGH ($P \leq 0.01$). Data presented as mean \pm SD.	...174
Table 6.1.	Performance and subjective descriptive match data (mean \pm SD).	...175
Table 6.2.	Correlations (\pm 90 % CI) between Δ CMJ and MEMS parameters and descriptive performance variables across the whole match ($n = 57$) and also adjusted for LOW ($n = 12$), MODERATE ($n = 24$) and HIGH ($n = 18$) bowling workloads.	...178-180
Table 6.3.	Between-match variation of MEMS parameters.	...181-182
Figure 6.3.	Session-RPE scores for each match throughout the season. *A significant difference from reduced match duration ($P \leq 0.05$). Data presented as mean \pm SD.	...183

Chapter 7. Neuromuscular, Biochemical, Endocrine and Perceptual Fatigue

Responses During Simulated Fast Bowling

Table 7.1.	Saliva and blood collection schedule; 24 hours pre-simulation to 24 hours post-simulation (spanning two consecutive days, typically separated by seven days).	...201
Figure 7.1.	Flight time (ms) for countermovement jump data as a result of simulated fast bowling loads; a: significant	...209

difference from pre to post ($P \leq 0.01$); b: significant difference from pre to post 24-h ($P \leq 0.05$); c: significant difference from post to 24-h post ($P \leq 0.05$). Data presented as mean \pm *SD*.

Table 7.2.	Performance and subjective CA-AIS fast bowling simulation data in all conditions (mean \pm <i>SD</i>).	...212- 213
Table 7.3.	Biochemical and endocrine concentrations across the time-course of recovery following CA-AIS fast bowling simulation in all conditions (mean \pm <i>SD</i>).	...215- 216
Figure 7.2.	Plasma Creatine kinase (CK) concentration ($\text{U}\cdot\text{L}^{-1}$) as a result of simulated fast bowling loads; a: significant difference from pre to post ($P \leq 0.01$); b: significant difference from pre to post ($P \leq 0.05$); c: significant difference from pre to post 24-h ($P \leq 0.05$); d: significant difference from post to 24-h post ($P \leq 0.05$). Data presented as mean \pm <i>SD</i>217
Figure 7.3.	Plasma Uric acid (UA) concentration ($\mu\text{mol}\cdot\text{L}^{-1}$) as a result of simulated fast bowling loads; a: significant difference from pre to post ($P \leq 0.05$); b: significant difference from pre to 24-h post ($P \leq 0.05$). Data presented as mean \pm <i>SD</i>218
Figure 7.4.	Plasma Urea concentration ($\text{mmol}\cdot\text{L}^{-1}$) as a result of simulated fast bowling loads. Data presented as mean \pm <i>SD</i>219

Figure 7.5.	Salivary Cortisol (sCort) concentration (ng·ml) as a result of simulated fast bowling loads; a: significant difference from pre to post ($P \leq 0.05$); b: significant difference from pre to 24-h post ($P \leq 0.05$); c: significant difference from post to 24-h post ($P \leq 0.05$); d: significant difference from pre to post ($P \leq 0.01$); e: significant difference from pre to 24-h post ($P \leq 0.01$); f: significant difference from post to 24-h post ($P \leq 0.01$). Data presented as mean \pm <i>SD</i>221
Figure 7.6.	Relationships between (A) Δ CMJ 24 h flight-time (ms) and perceptual well-being (AU; + 24 h), and (B) Δ CMJ 24 h flight-time (ms) and RPE (AU).	...223- 224
Figure 7.7.	Relationships between (A) Δ CK 0.5 h (U/L) and estimated TD (m), AU; + 24 h), (B) Δ CK 0.5 h (U/L) and perceptual well-being, and (C) Δ CK 0.5 h (U/L) and sRPE (AU).	...226
Figure 7.8.	Relationships between (A) Δ CK 24 h (U/L) and simulation duration (min), and (B) Δ CK 24 h (U/L) and number of deliveries bowled (<i>n</i>).	...227
Figure 7.9.	Relationships between (A) Δ CK 24 h (U/L) and estimated TD (m), (B) Δ CK 24 h (U/L) and PL (AU), and Δ CK 24 h (U/L) and HREI (AU).	...228
Figure 7.10.	Relationships between (A) Δ CK 24 h (U/L) and RPE (AU), and (B) Δ CK 24 h (U/L) and sRPE (AU).	...229

Acknowledgements

This doctoral thesis would not have been possible without the generous assistance of numerous people from both my professional and personal life. Professionally, I would like to say a huge thank you to my supervisors Dr Grant Abt and Dr Mark Fogarty, whose feedback, support, expertise and guidance throughout the last seven years have been invaluable. I would also like to give a special mention to Dr Ric Lovell and Dr Steve Barrett, who helped guide this thesis in its infancy. Steve, thanks for facilitating the professional relationship I developed with The Yorkshire County Cricket Club (YCCC). Furthermore, I would like to thank all the YCCC staff and players, past and present, for their efforts and support during data collection periods. Without you, this Ph.D. would not have been possible. Finally, I would like to thank many of my work colleagues from the Department of Sport, Health and Exercise Science, from the admin team to the Heads of Department.

Personally, I would like to thank my fiancée and soon to be wife Sally Pinder: she has been a pillar of support, love, positivity and encouragement throughout this process. She has been there in the final years of this Ph.D., experiencing the highs and many stressful rants! Furthermore, I would like to make a special mention of Dr Chris Wilcox, Dr Chris Towlson and Steve Hayes, who I consider mates ahead of work colleagues. Our “technician meetings” have been a welcome distraction from the Ph.D. It is now truly the end of an era!

Ultimately, a special mention must be made to my Mum and Dad, whose love, support (including financial) and encouragement have been ever-present throughout my life, without which none of this would have been possible.

This thesis is dedicated to my late father, William Minter Bray, gone but never forgotten.

List of Published Works

Peer-reviewed journal articles

1. Bray, J.W., Fogarty, M., Barrett, S., Lovell, R., and Abt, G. (2016). Using microtechnology to evaluate the between- and within-match variability of professional Twenty20 cricket fast bowlers. *Professional Strength and Conditioning – UKSCA*, 43(December), 19-26.

Conference proceedings

2. Bray, J.W., Fogarty, M., & Abt, G. (2015). The use of high-speed running and accelerometry in limited overs cricket to measure training load in fast bowling. Presented at The 5th World Congress of Science and Medicine in Cricket, Sydney, Australia.
3. Bray, J.W., Towlson, C., Hayes, S., Fogarty, M., & Abt, G. (2017). Relationships between training load, neuromuscular fatigue and creatine kinase following simulated fast bowling. Presented at The UK Strength and Conditioning (UKSCA) Annual Conference, Hinckley Island, Leicestershire, UK.

List of Abbreviations

%	Percent
Δ	Delta change
$^{\circ}\text{C}$	Degrees Celsius
$\mu\cdot\text{mol}\cdot\text{L}^{-1}$	Micromolar per litre
$\mu\text{g}\cdot\text{dL}^{-1}$	Micrograms per decilitre
μL	Microlitre
ABS	Absolute
AF	Australian football
AU	Arbitrary units
$\text{AU}\cdot\text{min}^{-1}$	Arbitrary units per minute
$\text{b}\cdot\text{min}^{-1}$	Beats per minute (HR)
CA-AIS	Cricket Australia –Australian Institute of Sport
<i>Cd</i>	Cliff's Delta
CI	Confidence interval
CK	Creatine kinase (U·L; units per litre)
CMJ	Vertical countermovement jump
COD	Change of direction
COM	Centre of mass
CV	Coefficient of variation
<i>d</i>	Cohen's effect size statistic
DJ	Depth jump
ECB	England and Wales Cricket Board
EIMD	Exercise induced muscle damage
ES	Effect size

FT	Flight-time (ms)
g	Earth's gravity ($9.81 \text{ m}\cdot\text{s}^{-1}$)
g	Grams
GPS	Global positioning systems
h	Hour
HDOP	Horizontal dilution of position
HIR	High-intensity running ($> 15 \text{ km}\cdot\text{h}^{-1}$)
HR	Heart rate ($\text{b}\cdot\text{min}^{-1}$)
HREI	Heart rate exertion index
HR_{LT}	Heart rate at lactate threshold (LT)
HR_{max}	Maximal heart rate
HR_{OBLA}	Heart rate at the Onset of Blood Lactate (OBLA)
HR_{peak}	Peak heart rate value
HRR	Heart rate reserve
HSRD	High-speed running distance ($\geq 14.4 \text{ km}\cdot\text{h}^{-1}$)
Hz	Hertz (cycle per second)
ICC	International Cricket Council
iTRIMP	Individualised training impulse
$\text{kCal}\cdot\text{m}^2\cdot\text{h}^{-1}$	Kilocalorie per square metre per hour
$\text{kg}\cdot\text{kg}^{-1}$	Kilogram per kilogram
$\text{kJ}\cdot\text{h}^{-1}$	Kilojoule per hour
km	Kilometres
$\text{km}\cdot\text{h}^{-1}$	Kilometres per hour
kp	Kiloponds
LOA	Limits of Agreement

LSRD	Low-speed running distance ($\leq 14.4 \text{ km}\cdot\text{h}^{-1}$)
m	Metre
$\text{m}\cdot\text{min}^{-1}$	Metres per minute
$\text{m}\cdot\text{s}^{-1}$	Metres per second
m^2	Square metre
MCC	Marylebone Cricket Club
MD	Multiday
MEMS	Micro-electro-mechanical system
$\text{mg}\cdot\text{L}$	Milligrams per litre
min	Minute
mL	Millilitres
$\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$	Millilitres per kilogram per minute
mm	Millimetres
$\text{mmol}\cdot\text{L}^{-1}$	Millimole per litre
ms	Milliseconds
n	Number
$n\cdot\text{min}^{-1}$	Number (frequency) per minute
$\text{ng}\cdot\text{mL}$	Nanogram per millilitre
NMF	Neuromuscular fatigue
O-B	Opening bowler
OD	One-day
ODI	One-day International
PL	PlayerLoad™
$\text{PL}\cdot\text{min}^{-1}$	PlayerLoad™ per minute
r	Pearson's product-moment correlation

RAND	Random (spell length)
REL	Relative
reps·min ⁻¹	Repetitions per minute
RH	Relative humidity (%)
RPE	Rating of perceived exertion
rpm	Revolutions per minute
RR	Risk ratio
RSI	Reactive strength index
s	Second
SAFT ⁹⁰	90-minute Soccer-specific aerobic field test
S-B	Support bowler
SCAP	Scapulae
sCort	Salivary cortisol
SD	Standard deviation
SE	Standard error
SEE	Standard error of the estimate
SJ	Squat jump
SPSS	Statistical package for the social sciences
sRPE	Session rating of perceived exertion
SSC	Stretch-shortening cycle
SSG	Small-sided game
SWC	Smallest worthwhile change (%)
T20	Twenty20
TD	Total distance
TE	Typical error

TEM	Technical error of measurement
THIR	Total high-intensity running
TL	Training load
TMA	Time-motion analysis
TRIMP	Training impulse
TSD	Total sprint distance ($\geq 18 \text{ km}\cdot\text{h}^{-1}$)
TSSC	Team sport simulation circuit
UA	Uric acid
VO ₂	Volume of Oxygen
VO _{2max}	Maximal Oxygen uptake
VO _{2peak}	Peak Oxygen uptake
W	Watts

Abstract

Recent professionalization, the emergence of, and ever-increasing popularity of limited overs cricket, have resulted in traditional playing schedules evolving and expanding. Consequently, players now compete for much of the year, experiencing periods of condensed fixtures. To meet these increased demands, the aforementioned contribute to effecting team performance and player health. Thus, the prevalence of injuries, especially amongst fast bowlers, has been shown and attributed to rises in competition workloads.

Therefore, the main aim of this thesis was to explore the application of micro-electro-mechanical systems (MEMS) to quantify the training load of fast bowlers. Furthermore, I sought to assess relationships between both internal and external training load variables and proposed markers of fatigue and recovery.

The first preliminary descriptive research study (Chapter 4) aimed to prospectively quantify fast bowling workloads during a typical season of professional domestic county cricket (April – September). Data were collected from fixture scorebooks, with descriptive bowling workloads determined by calculating frequencies of overs and deliveries bowled. This was further calculated dependant on both bowler classification (opening [O-B; $n = 2$] or support [S-B; $n = 6$]) and competition format (multiday [MD], One-day [OD] or Twenty20 [T20]), respectively. Significant differences were found in total number of overs (296.1 overs; 95% CI 37.8 to 554.4; $P = 0.03$) and deliveries (1764.8 balls; 95% CI 183.0 to 3346.7; $P = 0.03$) bowled between O-B and S-B, respectively. Multiday cricket was the only format where, significant differences between bowlers were found; total number of overs (289.9 overs; 95% CI 88.2 to 491.6; $P = 0.01$) and deliveries (1739.3 balls; 95% CI 529.3 to 2949.3; $P = 0.01$) bowled.

The aim of experimental study one (Chapter 5) was to assess the between-match and within-match between-over variability of external training load measures during T20 cricket competition. MEMS data were collected from eight fast bowlers in 17 matches of domestic T20 competition, spanning two seasons. MEMS variables were categorised into total distance (TD), low- ($\leq 14.4 \text{ km}\cdot\text{h}^{-1}$) and high- ($\geq 14.4 \text{ km}\cdot\text{h}^{-1}$) speed running distance, total sprint distance ($\geq 18 \text{ km}\cdot\text{h}^{-1}$), number of sprint efforts and PlayerLoad™ ([PL] arbitrary units; AU). Data were log-transformed to provide the coefficient of variation (CV; expressed as percentages). The between-match variability was greatest in high-speed running distance (32.9% CV), total sprint distance (49.0% CV) and number of sprint efforts (48.0% CV). Similarly, within-match between-over high-speed running distance (12.8% CV), total sprint distance (17.1% CV) and number of sprint efforts (12.3% CV) elicited the greatest variability, yet, this was markedly reduced compared to between-match observations. However,

TD and PL were found to be relatively stable measures of external training load (range; 5.5–13.3% CV), both between-match and within-match between-over.

Experimental study two (Chapter 6) investigated short-term neuromuscular fatigue (NMF) of fast bowlers and relationships to match performance during a typical season of professional academy OD limited overs cricket. Baseline measures of lower body NMF were assessed via flight time (ms) from a countermovement jump (CMJ). These measures were repeated every morning of competition; NMF was additionally assessed within 30-min after the cessation of the bowling innings (CMJ-FIRST or CMJ-SECOND). MEMS data were collected from six fast bowlers, with supplementary descriptive fast bowling workloads classifications (LOW, MODERATE and HIGH). There were significant reductions in flight time pre to post bowling innings (Δ 19 ms; $P = 0.008$). Moreover, similar reductions in flight time were found in LOW – MODERATE (Δ 30 ms; $P = 0.03$) and LOW – HIGH bowling workload groups (Δ 43 ms; $P = 0.003$), respectively.

Finally, experimental study three (Chapter 7) investigated neuromuscular, biochemical and endocrine markers of fatigue after four spells of simulated fast bowling. Eleven fast bowlers completed differing spells of simulated fast bowling based on the Cricket Australia-Australian Institute of Sport (CA-AIS) fast bowling skills test. NMF were assessed via flight-time from a CMJ; pre (-0.5-h) and post (+0.5 and +24-h) simulation, with blood (Creatine kinase; CK) and saliva (Cortisol; sCort) samples collected in parallel. During each simulated fast bowling trial (4-, 6-, RANDOM- & 10-overs), internal (heart rate exertion index [HREI]) and external (PL) training load was quantified using MEMS. There were small, significant reductions in CMJ flight time pre to post (Δ 21 ms; $P < 0.01$) and pre to 24-h post (Δ 8 ms; $P = 0.001$) simulation, respectively. Overs bowled appeared to significantly affect NMF for up to 24-h post simulation. Furthermore, changes in CK were found to best correlate with estimated TD ($r = 0.48$; $P = 0.002$) rating of perceived exertion (RPE $r = 0.47$; $P = 0.002$) session-RPE ($r = 0.48$; $P = 0.002$), HREI ($r = 0.45$; $P = 0.003$) and PL ($r = 0.41$; $P = 0.009$) 24-h post simulation, respectively.

The findings of this thesis demonstrate that during limited overs cricket, high-speed locomotive activity is highly variable amongst fast bowlers. Furthermore, fast bowlers are shown to experience short-term NMF, which appears to be magnified based on descriptive fast bowling workload characteristics. Collectively, these findings have importance for practitioners, who seek to facilitate performance by informed training prescription based on replicating match and training demands.

Key words: Training load; GPS; PlayerLoad™; neuromuscular fatigue; time-motion analysis

1. General Introduction

Cricket is a popular field-based bat-and-ball team sport comprised of two teams of 11 players, historically played within Commonwealth countries (McNamara, Gabbett, Chapman, Naughton, & Farhart, 2015a; McNamara, Gabbett, Naughton, Farhart, & Chapman, 2013; Orchard, James, Kountouris, & Portus, 2010). Although all players are required to field and bat during a match, thereby contributing to the overall performance of the team, each player has a specific skill set, which defines their role within the team (McNamara et al., 2013; Stuelcken, Pyne, & Sinclair, 2007). A traditional cricket team would consist of five specialist batsmen, one all-rounder, one wicket keeper and four specialist bowlers. These specialist bowlers can be broadly characterised by bowling speed: fast bowling (also known as pace bowling) and spin bowling. For the purpose of this thesis, the term fast bowler will be used and refers to bowlers who bowl fast, medium-fast or medium (deliver the ball with a fast run-up) as opposed to spin bowlers (Orchard et al., 2015). Typically, teams will play between one to five fast bowlers in any given match (McNamara et al., 2015a; Stuelcken et al., 2007).

Traditionally, cricket has been viewed as a leisurely, physically undemanding game, with many players being overweight (Woolmer, Noakes, & Moffett, 2009). However, recently, cricket has become a professional multimillion dollar sport, watched by billions worldwide, resulting in more than 100 countries now recognised by the international governing body for cricket, the International Cricket Council (ICC) (J. A. Johnstone & Ford, 2010; J. A. Johnstone et al., 2014). As a result of this increased professionalization, both internationally and domestically, traditional playing schedules have evolved and expanded to meet this demand. Therefore, professional cricketers are now inherently exposed to greater demands, reflected by

competing in a high number of matches ($n = \sim 100$ days) per season across multiple match formats, resulting in large, irregular variations in competition demands within short time frames (J. A. Johnstone et al., 2014; Noakes & Durandt, 2000; Orchard et al., 2010; Orchard, James, Portus, Kountouris, & Dennis, 2009). Ultimately, this schedule has resulted in players competing for much of the year, experiencing periods of condensed fixtures with shorter winter breaks, which is regarded as a threat to team performance and player health (Carling, McCall, Le Gall, & Dupont, 2016; Ekstrand, Walden, & Hagglund, 2004; Orchard et al., 2015). Even anecdotal reports feature/have featured in newspaper tabloids citing the scheduling demands placed on the modern international cricketer.

“I remember sitting in our annual captains’ conference at Lord’s each year and we would say that the sport needed to be careful about the amount of cricket we were playing” (Hussain, 2014).

It’s no great surprise to me that England are playing 17 Tests in nine months from April 2015 to January 2016. Equally we shouldn’t be surprised if the players themselves are too exhausted to complete the course” (Hussain, 2014).

“The break has come at a good time after three back-to-back Test matches. Going to Dubai will mentally give us a break from cricket and we can come back more refreshed” said Alastair Cook (Martin, 2016).

Unlike many other team sports, professional cricketers will compete in three different match formats, consisting of multiday (up to 5-days [MD]) and limited overs

(One-day [OD] and Twenty20 [T20]) cricket, respectively. Over the past 20 years, the playing schedule of professional cricketers comprised predominantly MD cricket and 50-over (OD) matches (McNamara, Gabbett, & Naughton, 2016). Multiday cricket is played with unlimited overs lasting up to five days (3 x 2 h sessions per day, with two innings per team). In these matches, bowlers may be required to bowl 50-overs (300 deliveries) or more over the four to five days, depending on the match outcome (Olivier et al., 2016; Orchard et al., 2015). However, recently, limited overs cricket has emerged and is now immensely popular. One-day matches are played with a maximum of 50 overs per innings and can last up to four hours (single team), where bowlers are restricted to bowling a maximum of 10-overs (Olivier et al., 2016; Orchard et al., 2015). Twenty20 is the most recent format of the game, introduced internationally in 2005, before domestic competitions were introduced a year later (2006). Domestic T20 competitions have grown substantially and have evolved into two of the largest cricket franchises: the Indian Premier League (IPL) in 2008 and the Big Bash League (BBL) in Australia in 2011, respectively. In these franchises, players are bought and traded across the world (McNamara et al., 2016; Orchard et al., 2015). Twenty20 matches have similar restrictions to OD cricket, whereby a maximum of 20-overs per innings is permitted, spanning up to 80 minutes, with bowlers restricted to bowling a maximum of 4-overs (Olivier et al., 2016; Orchard et al., 2015). As a result of the aforementioned competition restrictions, the physical demands of fast bowling can vary depending on both match type and the match-play strategy adopted by the team captain, thus collectively highlighting the importance of understanding the differences in match load and intensities between MD and limited overs OD cricket, respectively.

Given these scheduling issues, it is more likely that fast bowlers may experience the highest physical demands. Fast bowling is a highly dynamic skill, which requires the bowler to aim for consistency and accuracy while maintaining high ball speed (at the elite level, between 35 and 45 m·s⁻¹) and adjust movement patterns to generate different delivery types (bouncer, good length or Yorker) when required to the opposing batsman (Burnett, Elliott, & Marshall, 1995; Phillips, Portus, Davids, & Renshaw, 2012). The mark of a successful fast bowler is the continued ability to bowl fast and accurately for sustained periods of time, ultimately deceiving the batsman to achieve their wicket. In an effort to attain these high ball velocities, the fast bowling action is made up of a series of repetitive upper- and lower-body high-intensity muscle actions, which can typically be identified by four distinct parts, completed consecutively (J. A. Johnstone & Ford, 2010; Olivier et al., 2016) (Figure 1). Each delivery comprises a 15-30 m run-up, followed by the pre-delivery stride and delivery stride, prior to the follow-through, where the action ceases (6-7 s at a mean speed of 5 m·s⁻¹) (Taliep et al., 2003). There is 25-30 s recovery between deliveries and an 'over' consists of six consecutive deliveries by the same bowler (Devlin, Fraser, Barras, & Hawley, 2001). Under normal match conditions, fast bowlers would experience three to four minutes of active recovery (fielding) between overs (Devlin et al., 2001).



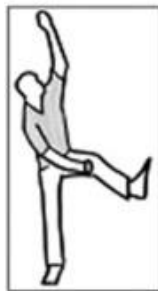
Run-up

The bowler walks or jogs, gradually increasing his speed, as he approaches the wicket. The run-up ends as he leaps into the air at the start of the pre-delivery stride. The run-up length varies between 15-30m.



The pre-delivery stride

The bowler jumps off his left foot and lands on the right or back foot.



The delivery stride

The bowler lands on his back foot with the body leaning away from the batsman. The delivery stride includes back foot strike, front foot strike and ball release.



Follow-through

The bowling arm follows through down the outside of the left thigh.

Figure 1.1. A schematic of the fast bowling action. Adapted from Olivier et al. (2016).

Traditionally, monitoring the physical demands of fast bowling has been limited to identifying the number of deliveries and/or overs bowled. Although this provides a simple, cost-effective and practical method, there is a possibility of inaccuracies, if the player is required to self-report, especially during training (McNamara et al., 2015a). In professional cricket, the physical demands of fast bowling have been associated

with injury likelihood (Dennis, Farhart, Clements, & Ledwidge, 2004; Dennis, Farhart, Goumas, & Orchard, 2003; Dennis, Finch, & Farhart, 2005). Therefore, identifying a valid method of quantifying bowling 'load' is vital in the management of fast bowlers. To that end, there is increasing interest in quantifying the physical demands experienced by cricketers during training and competition (Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009; Vickery et al., 2014). These studies have used time-motion analysis (TMA) as an objective method for quantifying the physical demands and player movement patterns. Traditionally, TMA was conducted in real time with a pen, paper and stopwatch (notational) or postgame utilising video recordings with or without customised computer software (Petersen, Pyne, Portus, & Dawson, 2009). However, recent developments in TMA now integrate wearable athlete tracking technologies of global positioning systems (GPS) and tri-axial accelerometers, allowing for a more practical, time-efficient approach to traditional TMA (R. J. Johnston et al., 2012). This integrated technology is now typically referred to as micro-electro-mechanical system (MEMS) and provides a further means of capturing movement patterns and quantifying the physical demands of athletes within sporting environments (Cummins, Orr, O'Connor, & West, 2013; Gustin, McLean, Spittle, & Breed, 2013; McNamara et al., 2015a; McNamara et al., 2013; Vickery et al., 2014).

The physical, psychological and locomotive demands placed on athletes during training and competition are usually referred to as their 'training load' (Bourdon et al., 2017). Measures of training load can be described/designated as physiological and psycho-biological responses (internal training load) and player movement patterns and activity profiles (external training load) (Cummins et al., 2013). Monitoring enables sport scientists and/or those working with cricketers to objectively quantify the level

of physical exertion and stress each player endures relative to their specific playing role in both training and competition (Cummins et al., 2013; Cunniffe, Proctor, Baker, & Davies, 2009; Waldron, Twist, Highton, Worsfold, & Daniels, 2011). Valid and reliable cricket-specific measures of training load and fatigue may assist by informing training prescription and recovery strategies, which may ultimately facilitate performance gains (Boyd et al., 2011) and reduce injury risk (Hulin et al., 2014).

Within cricket, specifically fast bowling, research incorporating MEMS technology has contributed to an increased understanding of the differences in match load and intensity across the different forms of competition and training (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2011; Petersen, Pyne, Portus, Karppinen, & Dawson, 2009). These studies have reported on both the variability in movement patterns during MD, One-day Internationals (ODI's) and T20 cricket and have reported on total distances covered across all forms of competition, respectively (Petersen, Portus, et al., 2009; Petersen, Pyne, Portus, Karppinen, et al., 2009). These findings show that fast bowlers covered the greatest total distances of any position, covering 22.6 km in a single day of MD (3 x 2 h sessions); 13.4 km in a OD (50-over) match and 5.5 km in a T20 match, respectively (J. A. Johnstone et al., 2014; Petersen, Pyne, Portus, Karppinen, et al., 2009). Aside from total distance, a global measure of training load, fast bowlers also covered the greatest distances in high-speed ($>14.4 \text{ km}\cdot\text{h}^{-1}$) locomotive activities and had at least 35% less recovery time between high-intensity efforts than players in other positions (Hulin et al., 2014; Petersen et al., 2010). Specifically, Petersen et al. (2010) highlighted that, during T20 cricket, there were 22% and 43% increases in hourly sprint distances for fast bowlers during OD limited overs and MD cricket, respectively (Stronach, Cronin, & Portus, 2014).

Recently, studies have started to report on tri-axial accelerometry (PlayerLoad™) within team sport environments (Barrett et al., 2015; Boyd et al., 2011; Boyd, Ball, & Aughey, 2013; Gastin, McLean, et al., 2013; McNamara et al., 2013). PlayerLoad™ (PL) is a movement variable that uses the accelerometer embedded within the MEMS device to measure the frequency and magnitude of vertical, anterior-posterior and medio-lateral accelerations to determine a player's external training load (Boyd et al., 2011; R. J. Johnston et al., 2012). Furthermore, these accelerometers have an increased sampling rate (100 Hz) compared to GPS (global displacement ranging from 1-10 Hz), making them more sensitive to subtle movements, such as the fast bowling action. Research has previously reported on the reliability of PL (Boyd et al., 2011) and its ability to quantify external training load in both competition and simulated team sport activity (Barrett et al., 2015; Boyd et al., 2013; R. J. Johnston et al., 2012). Despite its growing emergence in team sport settings, its practical application for monitoring cricket match play characteristics specifically, external training load within fast bowling is still in its infancy.

The demands of cricket match play were initially quantified using traditional TMA techniques. More recently, GPS and accelerometry technology have become an increasingly popular method for quantifying competition training load in cricket. Fast bowlers have previously been shown to cover the greatest total distances and spend the highest proportion of time engaged in high-speed locomotive activity. Despite this, only limited efforts have been made to determine the effectiveness of MEMS (GPS-accelerometry) technologies for monitoring the physical stress and markers of recovery in response to and following competition. This is increasingly important within cricket, as, unlike other team sports, the playing schedule has evolved and

expanded without any notable reduction in the number of fixtures. Furthermore, given that players compete in three different competition formats and fast bowling loads vary as a result of this, the need to establish accurate and reliable monitoring tools sensitive to fluctuations in training load is of paramount importance to minimise fatigue and optimise player performance capacity.

1.1. Aims

The main aims of this thesis are to:

- Describe the typical fast bowling workload characteristics during a professional county cricket season, differentiating between opening and support bowlers.
- Analyse the between- and within-match variability of external training load measures of professional fast bowlers during professional Twenty20 cricket.
- Monitor the short-term neuromuscular fatigue patterns of fast bowlers following one-day limited overs cricket, whilst highlighting between-match variability.
- Assess the short-term neuromuscular fatigue, biochemical and endocrine responses to a controlled fast bowling simulation.
- Examine the validity and practical application of micro-electro-mechanical system technology to monitor training load of fast bowlers.

2. Literature Review

2.1. The Physiological Requirements of Fast Bowling

Over the past decade, cricket has undergone a rapid change as it seeks to attract a more global audience (J. A. Johnstone et al., 2014; Noakes & Durandt, 2000). Consequently, the increased professionalism of preparing players for the physical demands of modern cricket is influencing the physical conditioning of players (M. R. Portus, Sinclair, Burke, Moore, & Farhart, 2000; Pyne, Duthie, Saunders, Petersen, & Portus, 2006). Therefore, it is probable that only the best prepared will perform better, more consistently with fewer injuries (Noakes & Durandt, 2000; Woolmer et al., 2009). However, currently, the prescription of fitness programmes has generally been based on educated guesses and intuition (M. R. Portus et al., 2000; Stronach et al., 2014). Moreover, when physiological data has been noted, it has been presented as a secondary outcome or in response to simulated fast bowling (Devlin et al., 2001; Duffield et al., 2009; Gore, Bourdon, Woolford, & Pederson, 1993; Minett, Duffield, Kellett, & Portus, 2012a, 2012b; M. R. Portus et al., 2000; Stretch & Lambert, 1999; Taliep et al., 2003), thus limiting the ecological validity.

One of the first studies to attempt a physiological analysis of cricket aimed to assess the energy expenditure of English and Australian cricketers during a five-match Ashes Test series (Fletcher, 1955). After calculating the total time players were engaged in competition for all Test matches (150 h), minus time lost to weather (46 h) and the ball being “out of play” (4 h), further analysis was undertaken, ultimately providing final calculations on the mean daily rate of energy expenditure of 86.4 kCal·m²·h⁻¹ (Fletcher, 1955; Noakes & Durandt, 2000). Relating this finding to the average cricketer, with a body surface area of 1.8 m², this corresponds to an energy

expenditure of $\sim 650 \text{ kJ}\cdot\text{h}^{-1}$. This data, together with data recorded using indirect calorimetry, allowed for comparisons to be made to other sports and cricketing activities, showing that the energy demands of Test-match bowling is only marginally greater than walking ($6 \text{ km}\cdot\text{h}^{-1}$), yet net bowling has a higher energy cost (Figure 2.1.). This finding led to the original understanding that cricket was physically undemanding and required more skill than fitness (Noakes & Durandt, 2000). However, it must be noted that the original calculations included time spent watching the game and, as a result, may not provide a true reflection of the energy demands of cricket, whereas that of net bowling appears to be more reflective of the physical demands of cricket.

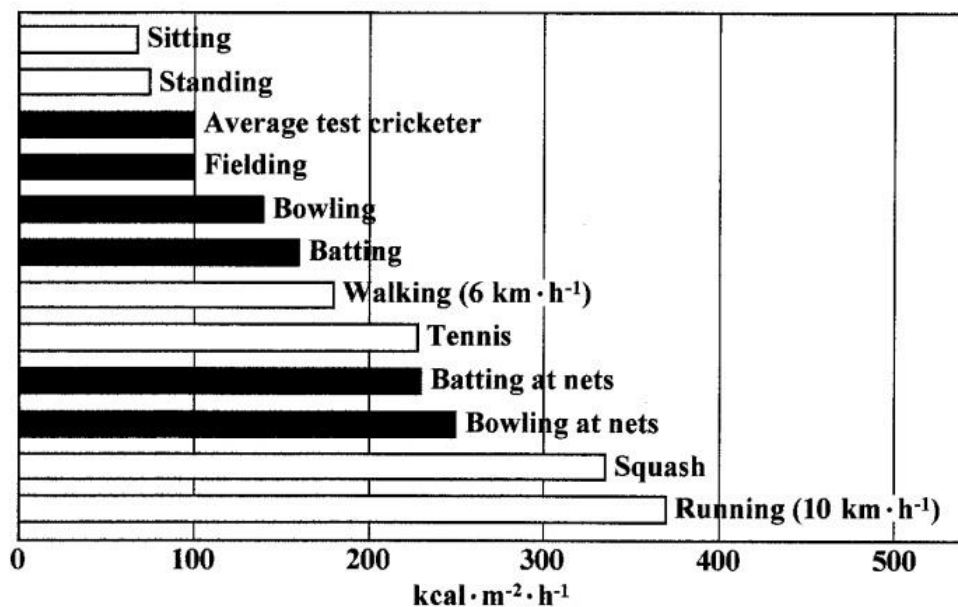


Figure 2.1. The energy demands of different cricketing activities compared to other sports and activities. Adapted from Fletcher (1955), Christie (2012) and Noakes and Durandt (2000).

When contrasted to other sports, it is perhaps presumed that cricket is less physically demanding. However, as demonstrated by Noakes and Durandt (2000), there were typically no significant differences found between international cricketers

or rugby union players (see Figures 2.2. & 2.3). A series of tests were performed to test against a range of aerobic (20-m shuttle run to predict maximal oxygen uptake, $\text{VO}_{2\text{max}}$), anaerobic (35-m sprint) and strength tests (leg and bench press). Unfortunately, the authors only partly detail testing protocols and present the results in figure format. Despite rugby being viewed as a more physically demanding sport requiring players to be well trained, in this study, international cricketers were found to be as aerobically (20-m shuttle run [estimated $\text{VO}_{2\text{max}}$]) and anaerobically fit (leg and bench press [$\text{kg}\cdot\text{kg}^{-1}$]) as rugby union players (Christie, 2012; Noakes & Durandt, 2000).

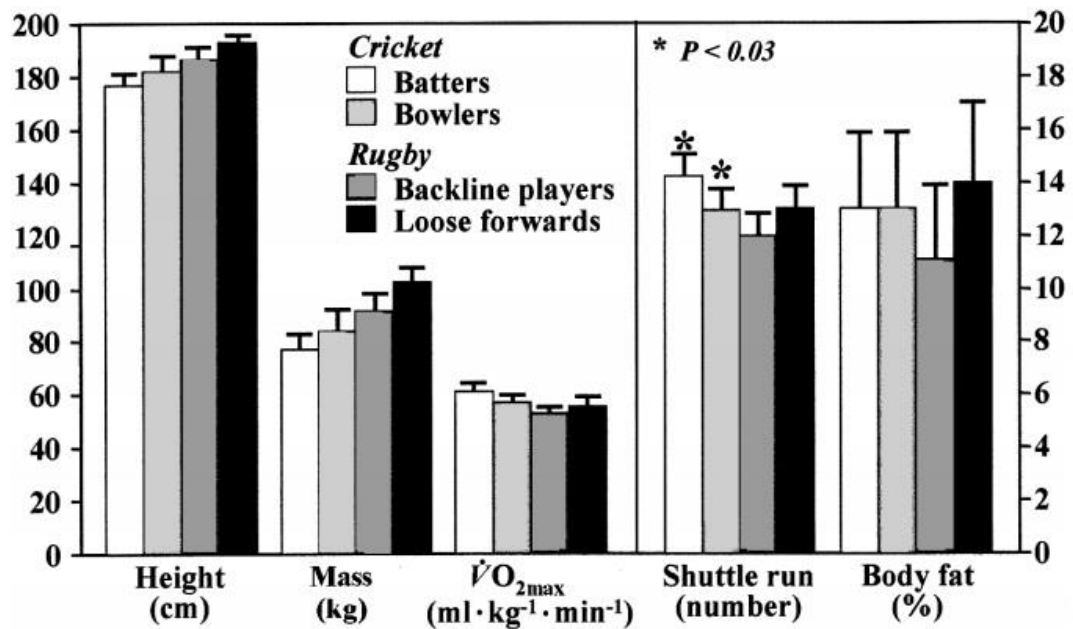


Figure 2.2. Comparison of aerobic physiological characteristics between South African international cricket and rugby players. Adapted from Noakes and Durandt (2000).

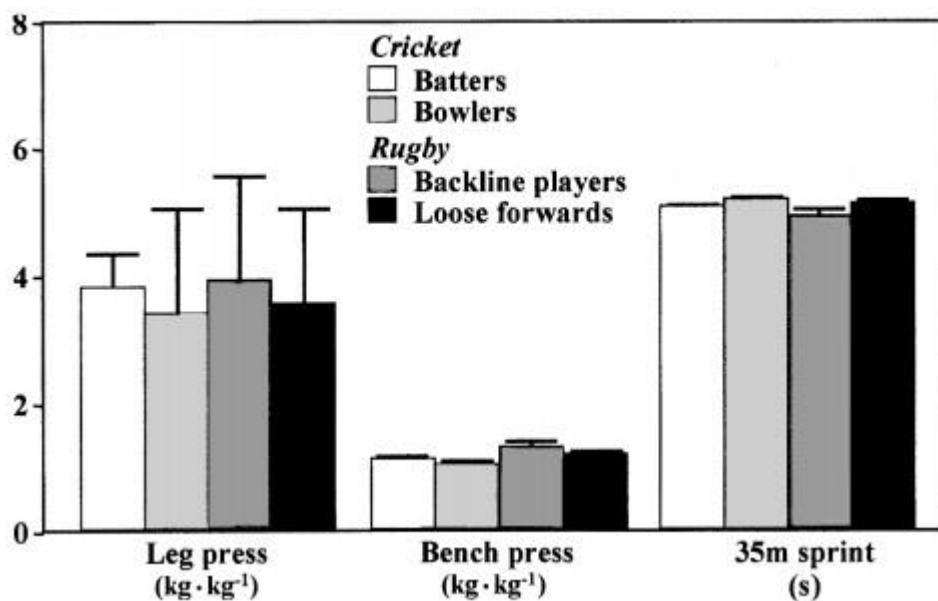


Figure 2.3. Comparison of anaerobic physiological characteristics between South African international cricket and rugby players. Adapted from Noakes and Durandt (2000).

Research exclusively identifying the physiological profile of fast bowlers is limited to a single study. J. A. Johnstone and Ford (2010) identified the anthropometric and physiological fitness characteristics of a professional cricket team in England during the pre-season phase. Fifteen professional cricketers were recruited (mean \pm *SD*; age 25 ± 5 years), with seven classified as medium/fast bowlers. Following a 10-minute standardised warm-up (including a mixture of light aerobic multidirectional movements and controlled dynamic stretches) players commenced a series of field-based fitness assessments. These included a multistage fitness test (predictive assessment of VO_{2max}), upper- (medicine-ball throw and timed press-up), lower-body strength (countermovement jump [CMJ]), sprint speed (sprint 1; 17.68 m and sprint 3; 3 x repeated sprints between same markers) and explosive power (repeated jump – reactive strength index [RSI]) tests, respectively. The results from this study show low

variance indicated by the confidence intervals (95% CI) in the predicted $\text{VO}_{2\text{max}}$ values with a moderate effect (ES) between fast bowlers and batsmen (predicted $\text{VO}_{2\text{max}}$; 54.1 [52.0 to 56.0] vs 56.1 [52.5 to 59.7] $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$; ES = 0.5). Small and moderate differences were found in sprint speed (s) in the sprint one (2.76 [2.72 to 2.81] vs 2.77 [2.69 to 2.85] s; ES = 0.1) and sprint three (9.62 [9.50 to 9.76] vs 9.76 [9.51 to 10.0] s; ES = 0.5) speed tests, respectively. Large differences were found in the two upper-body strength tests, bowlers out performed batsmen in the medicine ball throw (7.7 [7.3 to 8.2] vs 7.0 [6.9 to 7.1] m; ES = 1.3), whereas the opposite was found in the press-up test (54.7 [49.0 to 60.6] vs 80.4 [70.6 to 90.2] $\text{reps}\cdot\text{min}^{-1}$; ES = 2.4). No real differences were observed in the lower-body CMJ test. However, moderate differences were found in the RSI CMJ test (1.6 [1.5 to 1.8] vs 1.9 [1.5 to 2.3]; ES = 0.9). Earlier studies have also presented $\text{VO}_{2\text{max}}$ or $\text{VO}_{2\text{peak}}$ data, either estimated via 20-m shuttle run test (predicted $\text{VO}_{2\text{max}}$; $56 \pm 6 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) (Devlin et al., 2001) or via indirect calorimetry (incremental treadmill test; $\text{VO}_{2\text{max/peak}}$; 54 ± 6 or $60 \pm 10 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) (Burnett et al., 1995; Gore et al., 1993). Although the results from J. A. Johnstone and Ford (2010) expand on earlier predictive VO_2 findings (Burnett et al., 1995; Gore et al., 1993; Noakes & Durandt, 2000), it is important to acknowledge the differences in playing schedule and professionalization, which may influence the interpretation of this data with regard to the modern professional. Furthermore, these findings have also identified clear differences in the physical profile between fast bowlers and batsmen.

2.2. Methods of Quantifying Training Load

The monitoring of training load is a key component when seeking to control the training process (Joyce & Lewindon, 2014; Rebelo et al., 2012). Accurately evaluating the training load is fundamental for the planning and periodization of training, to

ensure players are meeting the prescribed training requirements and to minimise the risk of non-functional overreaching (fatigue lasting weeks to months), injury and illness (Halson, 2014; Rebelo et al., 2012; B. R. Scott, Lockie, Knight, Clark, & Janse de Jonge, 2013). Within sports of a continuous nature, this process can be achieved in several ways (Stagno, Thatcher, & van Someren, 2007). However, the intermittent nature of team sports presents particular difficulties, as players are mainly submitted to group training sessions aiming to develop team physical fitness and technical-tactical skills and may vary considerably in player numbers (Manzi, Bovenzi, Franco Impellizzeri, Carminati, & Castagna, 2013; Rebelo et al., 2012). This variability is also apparent throughout match-play where random discrete bouts of intensity and duration are also found (Stagno et al., 2007). Further challenges are placed on sport scientists and/or those working with cricketers who seek to monitor training load, as players will typically engage in three different forms of competition and have specialist roles within the team. Therefore, the quantification of the individual response to a given training load is vital to profile the training-related adaptive processes (Manzi et al., 2013; Stagno et al., 2007).

2.2.1. Overview of Training Load

The ability to quantify training load is fundamental to the process of evaluating the physical response of players to both training and match-play. Within cricket, training load can be described as either internal (e.g. heart rate [HR]-based methods or session rating of perceived exertion [sRPE]) or external (e.g. time, speed, distance covered, overs or balls bowled). This may allow sport scientists and/or those working with cricketers to understand the response of players to a prescribed training load, typically referred to as the “dose-response” relationship (Joyce & Lewindon, 2014).

Information regarding this relationship has grown exponentially in team sports and has been advocated as a key principle of training (Akubat, Barrett, & Abt, 2014; Ritchie, Hopkins, Buchheit, Cordy, & Bartlett, 2016; B. R. Scott et al., 2013). Physical training is typically quantified with reference to type, frequency, duration and intensity. However, it is the physiological stress imposed on the athlete referred to as the internal training load that determines the adaptations (Akubat et al., 2014; Brink, Nederhof, Visscher, Schmikli, & Lemmink, 2010; Joyce & Lewindon, 2014). The most commonly used methods for quantifying the internal training load involve recording HR as a measure of exercise intensity and RPE as a measure of relative training intensity (Alexiou & Coutts, 2008; Joyce & Lewindon, 2014).

Heart rate monitoring provides a non-invasive method of assessing exercise intensity, which in turn can be integrated with exercise duration to measure the internal training load in athletes. The validity of HR measurement has been established based on the near linear relationship between HR and the rate of oxygen consumption (VO_2) during steady state exercise (Alexiou & Coutts, 2008; Halson, 2014; Rebelo et al., 2012). The concept of training impulse (TRIMP) was introduced and developed by Banister, Calvert, Savage, and Bach (1975) as a possible strategy for integrating the components of training into a single arbitrary unit to quantify training load. A single TRIMP unit is calculated by incorporating training duration and HR reserve (HRR) together with a weighting factor based on the blood lactate response to exercise (Halson, 2014; Joyce & Lewindon, 2014). This weighting factor emphasises the greater stress associated with high-intensity exercise. Since the original Banister (1991) model, other variations on the theme have been developed. These include Edwards (1994) and Lucia's (2000) TRIMP, which are variations on arbitrary HR zones.

The original TRIMP concept was predominately used in endurance sport to provide a measure of internal training load (Akubat & Abt, 2011; Akubat et al., 2014; Banister et al., 1975). For example, TRIMP has been used in professional road cycling to investigate the “dose-response” of competitive time-trialling (Padilla, Mujika, Orbananos, & Angulo, 2000). When comparing five different duration time-trials, Padilla et al. (2000) were able to demonstrate the sensitivity and effectiveness of TRIMP to reflect physiological demands in relation to metabolic zones described using heart rate derived variables (HR_{OBLA} and HR_{LT}) when competing. Despite these findings supporting the use of TRIMP in endurance sport to some extent, where it is likely that the heart rate response will mimic the continuous nature of the sport, the use of TRIMP in team sport, noted for its stochastic nature, warrants further investigation (Stagno et al., 2007).

In an attempt to investigate the effectiveness of various HR-based training load methods in response to an intermittent team sport, Alexiou and Coutts (2008) investigated both the Banister (1991) and Edwards (1994) TRIMP, to quantify internal training load in women’s soccer. Unfortunately, these TRIMP methods have only shown relationships with each other and have not been reported to be related to changes in fitness or performance (Akubat et al., 2014; Impellizzeri, Rampinini, Coutts, Sassi, & Marcora, 2004). Furthermore, the magnitude of these relationships were increased as a result less intermittent, more aerobic-based training methods. It should also be noted that limitations exist with HR monitoring when it is applied to team sport environments, namely recording high-intensity intermittent exercise above maximal VO_2 (VO_{2max}), resistance training and plyometrics, respectively (Alexiou & Coutts, 2008; Joyce & Lewindon, 2014; Rebelo et al., 2012). Thus, the concept of an individualised TRIMP (iTRIMP), which reduces the issues associated with arbitrary

zones and generic weightings has been introduced (Halson, 2014; Manzi, Iellamo, Impellizzeri, D'Ottavio, & Castagna, 2009). This method has been shown to identify relationships between changes in aerobic fitness measures in soccer players (Akubat et al., 2014; Akubat, Patel, Barrett, & Abt, 2012).

Aside from HR methods, sRPE is another common method for assessing internal training load. Rating of perceived exertion is purported to provide a holistic or global indication of the training load and is indicative of both psychological and physiological stress (Halson, 2014; Rebelo et al., 2012). Foster et al. (2001) originally proposed the sRPE method for quantifying internal training load, which utilizes Borg's Category Ratio-10 (CR-10) RPE scale to measure exercise intensity. To calculate internal training load via this method, an athlete's RPE (1-10 scale) is multiplied by the duration of the session or match (in min). This method has been reported to be simple to administer, valid, reliable and correlates well with HR-based methods when seeking to quantify internal training load in team sport athletes (Alexiou & Coutts, 2008; Foster et al., 2001; Halson, 2014). However, there is very little evidence for the "dose-response" validity of sRPE in team sport players. Most 'validity' studies have simply correlated two or more methods of measuring training load against each other, rather than examining the relationships between the measure and changes in fitness and/or performance in a "dose-response" manner.

2.2.2 Time-Motion Analysis (TMA)

Traditionally, time-motion studies have been conducted in real-time using pen, paper and stopwatches or computers (notational) or analysed post-match using video recordings and, in some instances, specialist computer software (digitising) (Petersen et al., 2010). Over the last decade, advances in time-motion analysis (TMA) to

quantify the movement demands of athletes have resulted in various external measures to estimate exercise intensity and training load using physical-movement data (Coutts & Duffield, 2010). Consequently, microtechnology devices that include global positioning systems (GPS), tri-axial accelerometers and other movement sensors are now widely used in many sports to assess the external training load (Torreño et al., 2016). Typically, GPS data is often used to provide feedback on distance travelled and running speeds, whereas the accelerometer data summates the impacts endured by the athlete (T. J. Scott, Black, Quinn, & Coutts, 2012).

Time-motion analysis has been extensively used in team sports to record the rigours of training and competition (Lovell & Abt, 2012). However, in comparison to other team sports, cricket has not received the same research interest (Table 2.1.). Although early research (Fletcher, 1955) identified the average energy expenditure of Test match cricketers, subsequent TMA within cricket is a more recent practice (Petersen, Pyne, Dawson, Kellett, & Portus, 2011). Since the original Fletcher (1955) study, TMA has been used to quantify the movement activity of first-class cover point fielders (Rudkin & O'Donoghue, 2008) or Test and One-day international (ODI) batsmen scoring 100 runs (Duffield & Drinkwater, 2008) using video-based computerised methods. A significant consideration for traditional computerised video-based TMA is its time-consuming nature, which, in turn, results in relatively small sample sizes.

Table 2.1. Summary of early cricket-based time-motion analysis research.

Authors	Subjects	Methods	Results
Fletcher (1955)	English and Australian cricketers (5-match Ashes Series)	Mean daily energy expenditure calculated (based on typical body	Mean energy expenditure = 86.4 kCal·m ² ·h ¹

		surface area of 1.8 m ²)	
Duffield and Drinkwater (2008)	13 Test centuries 12 One-day scores above 80 runs (5 x 100 runs)	Computerised time-motion analysis (Part-Timer V1.1)	Duration to score 50-runs Test = 108.9 ± 26.6 min. One-day = 84.5 ± 17.7 min.
		Player movements were coded	Duration to score 100-runs Test = 213.4 ± 31.9 min. One-day = 135.5 ± 21.4 min.
			Test = 1.4% high-intensity activity
			One-day = 2.3 % high-intensity activity
Rudkin and O'Donoghue (2008)	<i>n</i> = 27 in-fielder observations (cover-point)	The first 10-overs of each session were analysed (morning, afternoon and evening).	Mean duration of each 10-over period was 37.6 ± 3.6 min.
		Real-time analysis to code player movements (CAPTAIN)	There were 361.3 ± 73.2 movement occurrences
			Estimated TD = 1483 ± 76 m.
			High-intensity activity represented 1.6 ± 0.8% match time

CAPTAIN = Computerised All-Purpose Time-motion Analysis INtegrated; TD = Total distance.

2.2.3. Global Positioning Systems (GPS)

In light of recent advances in mictotechnology, wearable athlete tracking technology allows for a more practical and time efficient approach to traditional TMA methods (R. J. Johnston et al., 2012; MacLeod, Morris, Nevill, & Sunderland, 2009; Petersen

et al., 2010). This technology, referred to as micro-electro-mechanical system (MEMS), typically incorporates GPS, tri-axial accelerometers and other movement sensors within a single portable device. These MEMS devices are now common place within cricket and other team sports and are superseding traditional TMA, as they provide practitioners with access to a plethora of objective external training load variables, with minimal disruptions to the player and training session (Bradley et al., 2015).

Global positioning systems utilise satellite-based navigation technology, continuously receiving time signals from a network of operational orbiting satellites (Cummins et al., 2013; MacLeod et al., 2009; Petersen, Pyne, Portus, et al., 2011). The satellites first set the clock on the GPS unit by synchronizing it with the atomic clock and then continuously send information relating to the exact time of the unit (Larsson, 2003; Petersen, Pyne, Portus, et al., 2011). By calculating the distance to at least four satellites, the unit position can be triangulated (Aughey, 2011; Larsson, 2003; Petersen, Pyne, Portus, et al., 2011). Movement speed can also be automatically determined by Doppler shift, which is calculated by identifying the change in satellite signal frequency due to the movement of the unit, relying on changes in position from a bird's eye view (Larsson, 2003). Originally, GPS technology was restricted to military users, but, in the 1980s, it was made available for civilian use (MacLeod et al., 2009). As a result of this development, GPS technology is now increasingly used in team sport settings to provide sport scientists and practitioners with real-time data pertaining to on-field player performance during training and competition (Cummins et al., 2013).

Continuing from the original TMA studies, the cricket literature now incorporates studies that have used MEMS technology, specifically including GPS data. This has contributed to an increased understanding of the differences in training load and intensity across the different forms of competition and training, related to medium-fast and fast bowlers (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009). However, since these early GPS studies, the literature has evolved again, and, as a result, incorporates accelerometry measures, namely PlayerLoad™ (McNamara et al., 2015a; McNamara, Gabbett, Chapman, Naughton, & Farhart, 2015b; McNamara et al., 2013), which will be discussed separately (Section 2.3.5 – 2.3.6.).

To date, Petersen and colleagues (2009) still provide the most extensive research into TMA of cricket and fast bowling between limited overs (one-day [OD] and T20) and multiday (MD) cricket, respectively. Petersen et al. (2009) sought to quantify the positional movement demands of T20 cricketers. Time-motion characteristics were collected from Australian state-level cricketers ($n = 18$) using 5 Hz GPS during four domestic T20 matches, totalling 30 innings. Descriptive movement characteristic match data were scaled to 80 minutes (time permitted for a T20 innings) for each fielding innings. By performing this “scaling”, the ecological validity should be questioned, as it may fail to give an accurate reflection of actual distances covered, if the fielding innings finished early. The results show that during an 80-minute “scaled” innings of T20 cricket, players covered a total of 6.4 to 8.5 km, with 0.1 to 0.7 km of this at sprinting velocities. Fast bowlers ($n = 4$) covered a total 8.4 ± 1.5 km, with 0.7 ± 0.2 km (9%) sprinting. Moreover, fast bowlers performed 11 more sprints (ES = 0.66; moderate), 33 more high-intensity efforts (running, striding, sprinting; ES =

0.60; moderate) and 13 seconds less recovery between high-intensity efforts ($ES = 0.60$; moderate) than fielders, respectively. It is important to identify that, although data is taken from a total of 30 innings, only four of those innings are data from fast bowlers, which may not accurately reflect typical match characteristics.

In research of a similar nature, McNamara and co-workers (2013) explored the differences in training and competition workloads between junior fast bowlers and non-fast bowlers. Time-motion characteristics were collected from two Australian age-group cricket squads (under 17 and under 19; $n = 26$; mean $\pm SD$; age 18 ± 13 years) during a seven-week physical preparation period (detailed below) and a 10-day intensified period of competition ($n = 2$ T20; $n = 3$ OD; $n = 2$ two-day matches) using 10 Hz GPS (MinimaxX; Catapult, Melbourne, Australia). Unfortunately, the authors fail to include any additional subject characteristics. One hundred and seventy match files were collected from fast bowlers ($n = 9$) and non-fast bowlers ($n = 17$), respectively. Competition data highlights that the distances covered by fast bowlers were greater than non-fast bowlers (median \pm interquartile range; 7.0 ± 3.9 km vs. 5.0 ± 3.7 km; Cliff's Delta \pm 90% CI = 0.36 ± 0.18 [moderate], 97% likelihood). Moreover, high-speed distances (≥ 18.0 km·h⁻¹) covered by fast bowlers were greater than non-fast bowlers (0.5 ± 0.5 km vs. 0.1 ± 0.1 km; Cliff's Delta \pm 90% CI = 0.90 ± 0.44 [large], 100% likelihood).

Petersen et al. (2009) examined the variability in movement patterns by an ODI fast bowler. Time-motion characteristics were collected from an international Australian fast bowler using 5 Hz GPS during 12 ODI's ($n = 6$ vs India; $n = 3$ vs Bangladesh; $n = 2$ vs Sri Lanka; $n = 1$ vs New Zealand). Like their T20 study, data were "scaled" (to 210-min; time permitted for an ODI innings) although actual match time data were also included (184 ± 41 min) to facilitate interpretation. Again, the

ecological validity of the data may be questioned, especially considering that an aim of this study was to describe the variability (coefficient of variation; % CV) of locomotive activities. Movement characteristics obtained show that, during a “scaled” ODI, the same fast bowler covered 15.9 ± 2.6 km (16% CV), with 1.1 ± 0.2 km sprinting (22% CV). Moreover, during the ODI’s 66 ± 11 sprints (17% CV) were performed, 191 ± 32 high-intensity efforts (17% CV), with 68 ± 12 seconds between high-intensity efforts (18% CV), respectively. Although both studies use the same locomotive and high-intensity effort classifications, both fail to detail basic subject characteristics.

In a similar theme to their earlier studies, Petersen et al. (2010) compared the movement patterns of cricketers in different playing positions and match formats. Time-motion characteristics were collected from Australian Centre of Excellence cricketers ($n = 42$; mean \pm SD; age 22 ± 3 years; body mass 84 ± 9 kg; height 1.81 ± 0.1 m) using 5 Hz GPS during 24 Tour matches ($n = 7$ T20; $n = 16$ OD; $n = 1$ three-day match). All data were recorded during the fielding innings and players were classified as either a bowler or fielder. Each player was further characterised as either a fast or spin bowler, wicket keeper, fielder or batsman. Fast bowlers performed 4 ± 1 and 7 ± 2 overs per innings of T20 and OD cricket, respectively, while, during MD cricket, 4 ± 2 overs were bowled per two-hour session. After ‘scaling’ the data to the hour, fast bowlers ($n = 18$) covered a total of 5.5 ± 0.4 km (mean \pm 90% CI) during an 80-min T20 innings. During a full 3.5 h OD innings, fast bowlers ($n = 24$) covered 13.4 ± 0.7 km and, in a full day’s play (3 x 2 h sessions) of MD cricket, covered 22.6 ± 2.1 km, respectively. The CV for total distance ranged between 9 and 27%. Moreover, during T20, fast bowlers met the criteria for repeated sprint activity (≥ 3 sprints with < 60 sec recovery, adapted from Spencer et al., 2004) on 3.3 ± 1.5

occasions with a mean of 4.8 ± 1.4 sprints per bout. In comparison, during OD and a MD innings, fast bowlers performed 6.2 ± 2.9 and 5.5 ± 4.0 repeated sprint bouts, with a mean of 5.0 ± 1.4 and 4.9 ± 0.7 sprints per bout, for OD and MD cricket, respectively. The CV ranged from 17 to 60% for number of sprint bouts.

In the final of these quantitative TMA match-play studies, Petersen and co-workers (2011) prospectively quantified movement patterns of state and international cricketers in two match formats (OD and MD) across two seasons. Time-motion characteristics were recorded from Australian international ($n = 12$; mean \pm *SD*; age 30 ± 4 years; height 1.85 ± 0.1 m) and state ($n = 42$; age 27 ± 3 years; height 1.83 ± 0.1 m) cricketers using 5 Hz GPS. A total of 263 GPS match files were collected from fast bowlers and fielders in 28 competitive matches (International: $n = 16$ ODI; $n = 3$ Test matches; state: $n = 6$ OD; $n = 5$ MD matches). As before, data were scaled to hourly values to allow for direct comparisons between match formats. Extrapolating the data to total distance covered in an innings of OD (ODI or domestic) or a session of MD (Test or first class) cricket, fast bowlers covered 14.1 ± 1.7 km (mean \pm *SD*) in OD and 15.0 ± 2.4 km in a session of MD cricket, respectively. The CV for total distance was one of the least variable measures and ranged between 14 and 32%. Fast bowlers covered 1.2 ± 0.3 km at sprinting velocities for both levels of performance, with sprinting the most variable time-motion characteristic (CV range 26 to 137%).

An important consideration when reviewing the literature is that, in the four Petersen et al. (2009; 2010; 2011; 2009) studies, the same 5 Hz GPS technology (MinimaxX; Catapult, Melbourne, Australia) was used to quantify the movement characteristics of Australian cricketers, allowing for direct comparisons to be made. However, although the recent McNamara (2013) study uses the same manufacturer (Catapult), both sampling frequency and speed classifications are different from the

earlier Petersen et al. studies, thus making comparisons difficult. Similarly, in other team sports, different speed classifications are also used, inhibiting comparisons to other team sports. Aside from total distance, which has been shown to be one of the least variable measures (% CV), fast bowlers also covered the greatest distances in high-speed locomotive activities and possessed the lowest exercise-to-recovery ratios across all formats of competition, which, in turn, displayed some of the highest variability (% CV). In addition to the variability in time-motion characteristics, research suggests that the validity and reliability of GPS-measured distances decreases at higher speeds. Section 2.3.4 of the literature review will provide a detailed account of the issues associated with using GPS technologies for quantifying external training load, with special reference to team sports.

2.2.4. Validity and Reliability of GPS

The validity and reliability of 1 Hz GPS devices were assessed via the use of a team sport simulation circuit (TSSC; e.g. walking, running, standing and zig-zag movements) (Coutts & Duffield, 2010; MacLeod et al., 2009), with data showing very strong correlations ($r \geq 0.99$) between the speed of the participants ($n = 9$) measured using timing gates and the values from the GPS unit (SPI Elite, GPSports, Canberra, Australia). Furthermore, no significant differences (mean difference \pm 95% limits of agreement [LOA] 0.0 ± 0.0) were found between the distance measured to complete the circuit by the GPS device (6821 ± 7 m) and the actual distance measured (6818 m) by a trundle wheel.

The advancements in GPS technology have resulted in 5 Hz units superceding the original 1 Hz units. As a result, 5 Hz units are commonly used within team sport environments, with it being suggested that, by increasing the sampling frequency, the

validity and reliability of GPS may be enhanced (Coutts & Duffield, 2010; R. J. Johnston et al., 2012). Research by Jennings and colleagues (2010a) sought to assess the validity and reliability of distance travelled using both 1- and 5 Hz GPS (MinimaxX; Catapult, Melbourne, Australia) during team sport movement patterns. Specifically, participants ($n = 20$) wore both units and were assessed during straight-line running (40 m) at four self-selected speeds (walking, jogging, striding and sprinting), during two separate change of direction (COD) courses (gradual [10 m; 3 x 90° COD] and tight [5 m; 7 x 90° COD]) and a modified simulated team sport running circuit (140 m) (D. Bishop, Spencer, Duffield, & Lawrence, 2001), respectively. The results show that, as speed of locomotion increased over a given distance (up to 40 m), validity decreased for both 1- and 5 Hz units. This was shown in both straight-line running (range ~9 to ~32% standard error of the estimate [SEE]) and COD courses (range ~9 to ~13% SEE), respectively. The validities (typical error [TE] \pm 90% CI) of total distances covered during the team sport simulation circuit at 1- and 5 Hz GPS were $3.6 \pm 0.6\%$ and $3.8 \pm 0.6\%$, respectively.

Research by Jennings et al. (2010b) explored the between-unit variation and differences in total distance travelled by the same player when wearing two 5 Hz GPS units (MinimaxX). Participants were monitored when performing either the team sport circuit ($n = 20$) or during three field hockey matches ($n = 8$), totalling 24 data files. During the team sport circuit, straight-line locomotion at four different speeds and two COD courses were assessed, as previously described (Jennings et al., 2010a). The percentage difference (\pm 90% CI) between units ranged from $9.9 \pm 4.7\%$ to $11.9 \pm 19.5\%$ for straight-line running at the four velocities and from $9.5 \pm 7.2\%$ to $10.7 \pm 7.9\%$ for the COD, respectively. The percentage difference in total distance and high intensity running distance covered during the team sport circuit were $11.1 \pm 4.2\%$ and

11.6 ± 9.3%, respectively. Similar results were observed (~10 ± 10%) during match play. In light of these findings, it was suggested that, to minimise the variability, the same participant should use the same unit in all trials.

Research by Johnston and colleagues (2012) explored the validity and reliability of two 5 Hz GPS units (MinimaxX) using both the TSSC (Coutts & Duffield, 2010) and flying 50-m sprint (F50) test, respectively. Although intra-unit reliability was not assessed, during both trials participants ($n = 9$ TSSC; $n = 4$ F50) wore both units simultaneously. The results from the TSSC show no significant differences ($P > 0.05$, percentage typical error of measurement [%TEM] = 2%) in total distance covered between the GPS total distance and the criterion measure (tape measure). Similarly, no significant differences ($P > 0.05$) were found in peak speed (%TEM = 5 to 10%). However, results from the F50 test show that most of these movement demands examined by GPS had a poor degree of error (%TEM = 20 to 60%).

Based on earlier studies related to GPS sampling rates and the inherent suggestions and expectations that 10 Hz GPS units would possess superior validity and reliability, research is now emerging exploring this speculation. Johnston et al. (2013) examined the validity and inter-unit reliability of 5- and 10 Hz GPS units to measure team sport movement demands. Participants ($n = 8$) wore both GPS units (5- & 10 Hz GPS; MinimaxX) and were required to complete the TSSC (Coutts & Duffield, 2010) ensuring a minimum of 10 data files were collected. Results showed no significant differences ($P > 0.05$) between the criterion measure (rigid tape measure) for distance covered during the TSSC (1320 m) and the inter-unit reliability of both 10 Hz (mean ± *SD*: unit 1 1331.9 ± 23.9; unit 2 1330 ± 23 m; %TEM = 1.3) and 5 Hz units (unit 1 1268.8 ± 24.4; unit 2 1325 ± 26 m; %TEM = 1.2), respectively.

However, significant differences were found between 10- and 5 Hz GPS for distance covered (1326 ± 24.6 vs. 1287.2 ± 17.2 m; $P \leq 0.01$) and peak speed (24.28 ± 1.54 vs. 23.96 ± 1.62 km·h⁻¹; $P \leq 0.05$), respectively. Interestingly, aside from total distance and peak speed, this study shows that both 10- and 5 Hz GPS units provide similar outcomes for most of the simulated athlete movement demands.

Although the majority of GPS research has focused on the validity and reliability of these units to measure distance covered in team sport movements, Petersen et al. (2009) examined the application of 1- and 5 Hz GPS units to monitor cricket-specific movement patterns. In this study, the authors compared the validity and reliability of three different GPS units (SPI-10 [1 Hz] and SPI-Pro [5 Hz]: GPSports, Canberra, Australia, MinimaxX [5 Hz]: Catapult, Melbourne, Australia). Twenty trials of cricket-specific locomotive patterns and distances (walking [≤ 7.2 km·h⁻¹] 8800 m, jogging [7.2 – 12.6 km·h⁻¹] 2400 m, running [12.6 – 14.4 km·h⁻¹] 1200 m, striding [14.4 – 18.0 km·h⁻¹] 600 m and sprinting [≥ 18 km·h⁻¹] 20- to 40 m intervals) were compared against criterion measures (400 m athletics track, electronic timing). Validity was quantified with the SEE and reliability estimated using typical error expressed as percentage CV. The validity of distance covered for walking up to striding velocities ranged from 1.7 to 3.8% (SEE) for the MinimaxX units, whereas the estimate in reliability ranged from 1.2 to 2.6% (CV) for the same velocities. However, for the same GPS units during sprinting, the validity for estimating distances over 20 – 40 m ranged from 14.4 to 23.8% (SEE), whereas the estimate in reliability ranged from 15.8 to 30% (CV) for the same distances. Therefore, caution is required when interpreting GPS data for shorter cricket-specific sprinting distances.

A growing number of studies have explored the validity and reliability of GPS during team sport movement patterns. In addition to these movement patterns

(straight-line running and multi-directional movements), Vickery et al. (2014) have sought to determine the reliability and accuracy of 5- and 10 Hz (MinimaxX) and 15 Hz (GPSports) GPS systems during unstructured movements typically found in cricket. These three GPS units were worn in duplicate and compared against a 22-camera VICON motion analysis system (100 Hz). Two participants completed 10 repetitions of 10 court/cricket- and field-based sport-respective drills, while concurrently wearing the GPS devices. Results show that during the cricket-specific run-a-three and fielding drills, there were no significant differences ($P > 0.05$) between the criterion measure (VICON) and the three GPS devices in total distance covered and in mean and peak speeds. However, during the fast bowling drills, significant differences were found between the VICON system and the GPS devices for both total distance (mean \pm SD: 5 Hz unit 1 19.7 ± 4.2 ; unit 2 18.0 ± 3.2 m; 10 Hz unit 1 13.7 ± 1.4 m; 15 Hz unit 1 14.5 ± 0.7 ; unit 2 13.5 ± 1.3 m) and mean speed (5 Hz unit 1 2.5 ± 0.6 ; unit 2 2.5 ± 0.6 m·s⁻¹; 15 Hz unit 1 3.1 ± 0.2 m·s⁻¹), respectively. The typical error (percentage CV) of the three cricket drills (run-a-three, fast bowling, fielding) for the 5- and 15 Hz GPS devices ranged from 5.5 to 22.1% CV for distance covered, mean speed 8.8 to 27.1% CV and peak speed 8.4 to 23.6% CV, respectively. Collectively, these results show that during unstructured movements typical of match play, all three GPS models underreport the total distance covered, when compared to the criterion measure.

In summary, it seems that, the higher the sample rate, the more valid the GPS becomes for measuring total distance. Furthermore, the reliability and validity of GPS to estimate longer distances initially appears to be acceptable (<10% CV) in both training

and competition. Despite this, the reliability of high-speed running data obtained from these devices decreases as speed increases.

Researchers and practitioners need to be aware of these aforementioned issues and implement methods ensuring collection of valid and reliable data. Specifically, to minimise the between-unit variability, each athlete should use the same unit in all training sessions and matches.

2.2.5. Accelerometry

Traditional systems used to quantify the training load in team sports (e.g. video) are questionable due to the intermittent nature of the sport and tend to be labour-intensive (Alexiou & Coutts, 2008; R. J. Johnston et al., 2012; Joyce & Lewindon, 2014; MacLeod et al., 2009; Petersen et al., 2010; Rebelo et al., 2012). Global positioning systems are a possible solution, as they can eliminate many of these issues (Boyd et al., 2011). However, as previously identified, these systems tend to display poor levels of validity and reliability when seeking to measure locomotive activity at high speeds over short distances (Jennings et al., 2010a). Furthermore, GPS also fails to account for specific sporting skills, namely the fast bowling action, which is a highly dynamic skill, made up of a series of repetitive upper- and lower-body high-intensity muscle actions (J. A. Johnstone & Ford, 2010; Olivier et al., 2016). Generally, the fast bowling action is quantified using descriptive statistics, namely balls and overs bowled and has traditionally been used to report on fast bowling workloads and associated injury risks. The inability to adequately quantify these activities may greatly underestimate the physical demands of fast bowling in cricket, therefore providing an objective measure of external workload may be beneficial.

Tri-axial accelerometers are highly responsive motion sensors, which can be used to measure the frequency and magnitude of movements in three dimensions (anterior-posterior, mediolateral and longitudinal) and have been used extensively in clinical populations (Boyd et al., 2011, 2013; Kozey, Lyden, Howe, Staudenmayer, & Freedson, 2010). It is suggested that tri-axial accelerometry may offer an additional means of quantifying external training load by possessing a superior sampling frequency (100 Hz) compared to GPS alone, may have the potential to represent gross fatiguing movements, not just locomotive activity, and is relatively unobtrusive (Boyd et al., 2011; Montgomery, Pyne, & Minahan, 2010). Although the application of tri-axial accelerometry in professional sport is still in its infancy, it is becoming increasingly apparent within the team sport environment.

Specifically, the accelerometer-derived variable using the vector magnitude algorithm, termed PlayerLoad™ (Barrett, Midgley, & Lovell, 2014; Barrett et al., 2015; Boyd et al., 2011, 2013; B. R. Scott et al., 2013) has seen a rise in popularity. PlayerLoad™ is an arbitrary unit that is calculated using the square root of the sum of the squared instantaneous rates of change in acceleration in each of the three vectors (X [forward/backward], Y [side/side] and Z [up/down] axis) and then divided by 100 (Figure 2.4.) (Boyd et al., 2011; Montgomery et al., 2010).

$$\text{Player load} = \sqrt{\frac{(a_{y1} - a_{y-1})^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}{100}}$$

where

a_y = Forward accelerometer

a_x = Sideways accelerometer

a_z = Vertical accelerometer

Figure 2.4. PlayerLoad™ equation. Adapted from Boyd et al. (2011).

To date, McNamara and colleagues are the only authors to have investigated the application of PlayerLoad™ in cricket, specifically providing data from training and competition in both junior and senior cricketers (McNamara et al., 2015b; McNamara et al., 2013). In the earlier of the two studies (McNamara et al., 2013), data were collected from professional age-group cricketers (mean \pm SD: age 18 ± 1) to profile and identify key training load variables of both fast bowlers and non-bowlers in training ($n = 83$ data files) and competition ($n = 170$ data files). In addition to GPS metrics (10 Hz), data were collected from the tri-axial accelerometer (MinimaxX; 100 Hz) embedded within the MEMS unit to calculate PlayerLoad™. Comparisons between fast bowlers and non-fast bowlers identified that PlayerLoad™ was greater in fast bowlers during competition (median \pm interquartile range 912 ± 481 vs 697 ± 424 ; Cliff's Delta \pm 90% CI = 0.32 ± 0.16), but the differences were unclear during training (median \pm interquartile range 703 ± 450 vs 598 ± 427 ; $Cd = 0.16 \pm 0.2$), respectively. Furthermore, when PlayerLoad™ is expressed relative to playing time (PlayerLoad™·min⁻¹), similar observations are found in both competition (median \pm interquartile range 9 ± 3 vs 6 ± 3 ; $Cd = 0.49 \pm 0.24$) and training (median \pm interquartile range 7 ± 3 vs 6 ± 3 ; $Cd = 0.21 \pm 0.2$). The descriptive PlayerLoad™ data from this study shows that fast bowlers completed greater external training loads compared to non-fast bowlers in both competition and training. Moreover, given the greater certainty in differences during competition, it is likely that the differences in PlayerLoad™ can be attributed to the act of fast bowling itself.

Research by McNamara and co-workers (2015b) assessed the between-bowler variability in PlayerLoad™ and other bowling performance variables across repeated spells of fast bowling. Data were collected from seven professional fast bowlers (mean

$\pm SD$: age 22 ± 3) during outdoor net training sessions (2 x 6-over spells). PlayerLoad™ was assessed between bowler for variability (% CV) and for differences across consecutive overs, bowling spells and individual deliveries, respectively. The CV ($\pm 90\%$ CI) across the 12-overs showed no significant differences in relative peak PlayerLoad™ (calculated as the sum of scores over 6-balls [1-over]) between bowlers (% CV 1.9 [1.7 to 2.1]; $P = 0.15$). Similarly, no significant differences were observed between bowlers on an individual ball basis across the 12-overs (% CV 2.4 [2.3 to 2.5]; $P = 0.29$). This was the first study to explore the practical application of PlayerLoad™ within cricket fast bowling using MEMS. Over repeated spells of fast bowling, PlayerLoad™ displayed a consistently low variability and therefore may provide further assistance in the monitoring of external training load in cricket.

Due to the paucity of studies examining the use of PlayerLoad™ in professional cricket, the remainder of this section will discuss research from other team sport environments. Research by Barrett et al. (2015) sought to assess the acute changes in overall PlayerLoad™ during a standardized 90-min soccer match play simulation (SAFT⁹⁰) (Lovell, Midgley, Barrett, Carter, & Small, 2013), consisting of two 45-min halves (3 x 15-min fixed activity profile per half). Further analysis was performed to account for the influence of unit positioning (scapulae [SCAP] and centre of mass [COM]). Data were collected from both semi-professional ($n = 5$) and university level ($n = 15$) soccer players (mean $\pm SD$; age 22 ± 3 years; body mass 78.9 ± 9 kg; height 1.80 ± 0.1 m) who completed three trials of the SAFT⁹⁰ (1 familiarisation, 2 experimental). There were no significant differences between the first and second half for PlayerLoad™ determined for SCAP (514 ± 58 vs 512 ± 57 ; $P = 0.8$; ES = 0.19) and COM (727 ± 82 vs 724 ± 88 ; $P = 0.1$; ES = 0.19), respectively. Furthermore, the SCAP-derived differences in PlayerLoad™ increased significantly

from baseline (0-15-min period) and displayed significant differences ($P \leq 0.01$) in each of the three periods in the first half and the final 15-min period of the second half. Although the authors identify significant differences and present effect sizes, indicating the magnitude of these differences, this is listed as a range for all 15-min data periods. Presenting the findings like this inhibits the interpretation of specific within-match changes in movement strategy, negating the practical applications of fatigue management, which have been proposed by the authors. Nonetheless, these findings tend to suggest that unit placement specifically at the SCAP is effected by upper-body kinematics influencing PlayerLoad™. These findings contribute to the widely accepted unit placement in cricket, where there is an increased importance in the upper-body kinematics during the bowling action.

Research by Montgomery et al. (2010) quantified and characterised physical (via accelerometry) and physiological responses to basketball. Data were collected from junior elite basketball players ($n = 11$; mean \pm *SD*; age 19 ± 2 years; body mass 87.9 ± 15 kg; height 1.91 ± 0.1 m) in both competition and training. A total of 128 on-court competition periods and 295 training drills ($n = 190$ defensive; $n = 57$ offensive; $n = 48$, 5on5 scrimmage) were collected and normalised relative to playing time ($\cdot\text{min}^{-1}$). Results from this study highlight only trivial differences in accelerometry data normalised for playing time between offensive and defensive (% difference \pm 90% CI; 10 ± -25 to 59 %; ES = 0.26) drills. However, substantially moderate differences were observed when the same comparisons were made between competition and the 5on5 or offensive and defensive training drills (85 ± 32 to 160 %; ES = 1.17), respectively. Although this study is predominantly descriptive in nature, it does support the application and sensitivity of accelerometry, as it can distinguish between physical demands of training and competition. Unfortunately, unlike other studies, the

accelerometer was positioned at the lumbosacral region (COM), thus inhibiting some comparisons.

Similarly, research by Boyd et al. (2013) used PlayerLoad™ specifically adjusted for playing time (PL·min⁻¹) to profile Australian football (AF) and identify differences in playing position and playing levels in both competition and training. Participants were from a single AF squad including both elite ($n = 19$; mean \pm *SD*; age 25 ± 4 years; body mass 87.9 ± 9 kg; height 1.87 ± 0.1 m) and sub-elite ($n = 21$; age 21 ± 2 years; body mass 87.7 ± 18 kg; height 1.85 ± 0.01 m) players. Data were collected from both levels of competition ($n = 24$ elite; $n = 29$ sub-elite) and during whole team training sessions ($n = 32$). Comparisons in playing position identified that, irrespective of playing standard, midfielders (mean \pm *SD*; elite 16.0 ± 4.2 ; sub-elite 15.1 ± 2.0) recorded the highest PlayerLoad™ values of all positions (range 10.3 to 14.9 PL·min⁻¹). Furthermore, elite players accumulated a higher PlayerLoad™ than sub-elite players (difference 4.6 to 18%; ES 0.2 to 0.9). Moreover, when the same comparisons were made between training and competition, only small-sided games (15.5 ± 5.0 PL·min⁻¹) and match practice (13.0 ± 2.9 PL·min⁻¹) were able to achieve near competition PlayerLoad™ values. Although this study was descriptive in nature, these results show that accelerometers, specifically PlayerLoad™ have the potential to differentiate between external training load in both competition and training, thus suggesting their practical application in a team sport environment.

Research by Scott and colleagues (2013) provided comparisons of both internal (HR-based TRIMP methods & session-RPE) and external (GPS-accelerometry) training load variables during professional soccer training (in-season). Data were collected from a single professional soccer team ($n = 15$; mean \pm *SD*; age 25 ± 5 years; body mass 77.6 ± 8 kg; height 1.81 ± 0.1 m), encompassing attacking,

midfield and defensive playing positions, across 29 on-field training sessions ($n = 97$ individual data files). Measures of internal and external training load were analysed and correlation coefficients calculated ($r \pm 95\%$ CI). All internal versus external training load variables displayed significant ($P < 0.01$) relationships. Specifically, large relationships were found between PlayerLoad™ and sRPE ($r = 0.84$ [0.77 to 0.89]), when examining Banister's ($r = 0.73$ [0.62 to 0.81]) and Edwards' ($r = 0.80$ [0.71 to 0.86]) TRIMP, respectively. Furthermore, a significant large relationship was found between total distance (derived from GPS) and PlayerLoad™ ($r = 0.93$; $P < 0.01$).

In a similar study, T. J. Scott et al. (2012) provided comparisons between internal (HR-based TRIMP methods and session-RPE [both CR 10 and CR 100]) and external (GPS-accelerometry) training load variables during skill based Australian Football training sessions. Data were collected from a professional AF team ($n = 21$; mean \pm SD; age 19 ± 2 years; body mass 83.9 ± 8 kg; height 1.88 ± 0.1 m). Due to the limitations in GPS availability, data were only recorded from 10 participants over 18 ± 3 sessions. Individual correlation coefficients ($r \pm 95\%$ CI) were performed between both internal (CR 10, CR100 and both TRIMP methods) and external (MEMS) training load methods. All correlations were statistically significant ($P \leq 0.05$), with strong relationships found between session-RPE and PlayerLoad™ for both CR10 ($r = 0.83$) and CR100 ($r = 0.80$), respectively. Collectively, these two studies suggest that PlayerLoad™ provides an acceptable measure of external training load. However, research is still lacking when seeking to explore the “dose-response” of PlayerLoad™ to assess changes in fitness or physical performance in different forms of team sport training.

Although not PlayerLoad™ per se, research by Gatin, McLean, et al. (2013) and, more recently, McNamara and colleagues (2015a) used similar technologies (tri-axial accelerometry, gyroscope and magnetometer) embedded in MEMS devices' (MinimaxX, Catapult) to explore the application of PlayerLoad™ in grading the severity of tackles and the fast bowling count function versus real-time notational analysis. Professional team sport athletes ($n = 20$ Australian football; $n = 12$ fast bowlers) were observed either during competition ($n = 4$ AF matches; $n = 214$ fast bowling data files) or during a series of bowling activities during net training ($n = 288$ data files). Data from Gatin, McLean, et al. (2013) showed that peak PlayerLoad™ was significantly greater in high (mean \pm *SD*; PL 7.5 ± 1.7 ; $P < 0.01$) compared to medium (PL 4.9 ± 1.5 ; $P < 0.01$) and low intensity tackles (PL 4.0 ± 1.3 ; $P < 0.01$), respectively. Results from McNamara et al. (2015a) showed no significant differences ($P = 0.34$) between the direct bowling counts (notational) and the MEMS detection in both training and competition. Moreover, a very strong, near perfect relationship ($r = 0.99$) was also found between direct bowling counts and MEMS detection in both training and competition. Collectively, these findings can support the practical application and ecological validity of MEMS technology (and PlayerLoad™) in recording key external training load variables in both Australian football and cricket, respectively.

Early research (Boyd et al., 2011) assessed the reliability of PlayerLoad™ in both laboratory and field-based environments. First, 10 accelerometers (MinimaxX, 100 Hz) were positioned in a static environment. Subsequently, these accelerometers were subjected to two standardised mechanical shaking trials. During these trials, eight accelerometers were simultaneously shaken at a frequency of 3 Hz (trial 1; waveform = 0.5 g) and 8 Hz (trial 2; waveform = 3 g), respectively. Each unit was subjected to

10 trials of 10-seconds for each trial (1 and 2). Following the static trials, these devices were attached to 10 athletes, who completed a 180-min team sport training session, involving large volumes of high-intensity activities, jumping and changes in direction. Twenty accelerometers were assigned to ten semi-professional Australian football players (mean \pm *SD*; age 23 ± 2 years; body mass 83.0 ± 5 kg; height 1.82 ± 0.1 m) and data were collected during nine competitive matches (pre-season and league). Two units were assigned to each player, one positioned proximally and the other distally, swapping placement after each match. Data were analysed to produce both within-device reliability (mean difference between trials) and between-device reliability (mean difference between devices) and the magnitude of difference expressed as a coefficient of variation (% CV). Data from both parts of the laboratory trials showed highly acceptable reliability in both within- (static: % CV 1.01; dynamic [0.5 g]: 0.91; [3 g]: 1.05) and between-device tests (static: % CV 1.10; dynamic [0.5 g]: 1.04; [3 g]: 1.02), respectively. Between-device reliability of accelerometers collected during the AF match trials also indicated highly acceptable reliability (% CV 1.9). Furthermore, each pair of devices (on the same individual) produced a near perfect relationship ($r = 0.996$ to 0.999). Collectively, these findings support the practical application of accelerometers, specifically PlayerLoad™, by indicating acceptable reliability (% CV < 2.0) in both laboratory and applied sporting environments.

In addition to identifying the acute alterations in PlayerLoad™ (see Section 2.3.5.), Barrett and colleagues (2014; 2015) explored the test-retest reliability of PlayerLoad™ during a standardized bout of treadmill running (starting speed of 7 km·h⁻¹, on an incline of 1%, subsequently increasing in speed by 0.1 km·h⁻¹ every 6 seconds, until volitional termination [note: the authors excluded any data > 16 km·h⁻¹]) and a soccer simulation (SAFT⁹⁰), respectively. Furthermore, these studies also

explored the effect of accelerometer position (SCAP or COM) on PlayerLoad™ data. Test-retest reliability was reported as either intraclass correlation coefficient (ICC), coefficient of variation (% CV) and/or differences in means presented by traditional null-hypothesis testing. Analysis of test-retest data following the standardised treadmill running protocol displayed no significant differences with moderate to high levels of reliability between trials at both SCAP (ICC 0.93; % CV 5.9; $P = 0.94$) and COM (ICC 0.97; % CV 5.2; $P = 0.92$), respectively. Furthermore, following the soccer simulation, the systematic bias was indicated by consistent low degree of variability at both SCAP (% CV 3.8) and COM (% CV 3.6), respectively. This data extends on previous findings and suggests that irrespective of unit positioning, practitioners can be confident in using PlayerLoad™ to quantify external training load, both during treadmill running and simulated team sport. However, it is recommended that caution be used when making between-athlete comparisons, as PlayerLoad™ was shown to account for differences in individual running gait with increasing locomotive speeds.

In light of this abundance in data, the challenge lies in identifying the variables that provide valid and reliable information pertaining to both internal and external training load. A possible solution to achieve this is to combine data from MEMS devices (Weaving, Marshall, Earle, Nevill, & Abt, 2014) specifically, using heart-rate, GPS and PlayerLoad™ data and subjective measures (session-RPE) to quantify the training load experienced by cricket fast bowlers.

2.3. Overview of Neuromuscular Fatigue (NMF)

Training loads are adjusted throughout the training cycle to either increase or decrease fatigue depending on the training phase (e.g. pre-season or competition phase) (Fowles, 2006; Halson, 2014). Therefore, coaches and conditioning staff should

understand and effectively manage the fatigue-recovery process, which, in turn, will allow for the appropriate administration of training loads to maximise competition performance (Fowles, 2006; Halson, 2014; Wehbe, Gabbett, Dwyer, McLellan, & Coad, 2015). Although performance in the activity itself has been suggested to be the most specific indicator of an athlete's sport specific neuromuscular performance readiness, its long-term assessment may be impractical (P. A. Bishop, Jones, & Woods, 2008; Gathercole, Sporer, Stellingwerff, & Sleivert, 2015b). Alternatively, quantifying fatigue can provide meaningful information pertaining to the preparation and readiness of athletes to train and compete, which may be beneficial for overall season performance (Gastin, Meyer, & Robinson, 2013; McLean, Coutts, Kelly, McGuigan, & Cormack, 2010; Wehbe et al., 2015). Measures of neuromuscular function and biochemical markers (see Section 2.5.) are often used to assess recovery after team sport activity owing to its usefulness in monitoring low-frequency fatigue, resulting from high-intensity, repetitive eccentric or stretch-shortening cycle (SSC) activities (Joyce & Lewindon, 2014; McLean et al., 2010; McLellan & Lovell, 2012; McLellan, Lovell, & Gass, 2010; C. P. McLellan, D. I. Lovell, & G. C. Gass, 2011b; Twist & Highton, 2013). The phenomenon of neuromuscular fatigue (NMF) has long-lasting, detrimental effects on force-generating capacity and is measured objectively as an acute reduction of performance during exercise (Cairns, Knicker, Thompson, & Sjogaard, 2005; Joyce & Lewindon, 2014). Furthermore, an accumulation of fatigue or incomplete recovery can have a large influence on performance, ultimately resulting in underperformance, especially during periods of regular competition (McLean et al., 2010).

It has been proposed that field tests to monitor neuromuscular function in an elite sporting environment should be valid, objective, simple to administer, highly

reliable, practical for application in the field, and require minimal technology, while preventing the minimal amount of additional fatigue (Halsen, 2014; Twist & Highton, 2013; Wehbe et al., 2015). Consequently, short maximal-effort performance tests, such as vertical jump tests (countermovement/squat jump) or sprint performance (20-meters) are often utilised in the sporting domain (Halsen, 2014; Twist & Highton, 2013). Vertical jump procedures are useful, because they reflect the stretch-shortening capacity of the lower limb musculature and have the ability to evaluate muscle fatigue (Komi, 2000; Twist & Highton, 2013). Consequently, the countermovement jump (CMJ) has been one of the most used protocols in high-performance sport for monitoring neuromuscular status, as it uses a combined eccentric/concentric muscle action, as defined by a stretch-shortening cycle (Claudino et al., 2016; Cormack, Mooney, Morgan, & McGuigan, 2013; Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; Duffield et al., 2009; Joyce & Lewindon, 2014; Komi, 2000; McLean et al., 2010; C. P. McLellan et al., 2011b; McNamara et al., 2013; Mooney, Cormack, O'Brien B, Morgan, & McGuigan, 2013; Slinde, Suber, Suber, Edwén, & Svantesson, 2008). Moreover, the similarities in neuromuscular function between a CMJ and running suggest that the assessment of CMJ performance may be suitable for NMF monitoring in running-based sports (Wehbe et al., 2015). Specific CMJ performance variables include mean power, peak force, jump height, flight time, contact time and can be determined via the use of contact mats, portable or non-portable force platforms, rotary encoders and, most recently, smart phone applications (Balsalobre-Fernández, Glaister, & Lockett, 2015; Claudino et al., 2016; Halsen, 2014; Taylor, Chapman, Cronin, Newton, & Gill, 2012; Twist & Highton, 2013). Typically, CMJ tests are often performed using a contact mat, which measures flight time and calculates jump height (Slinde et al., 2008).

Countermovement jump tests offer a high level of practicality and reliability, while requiring minimal physiological strain, allowing for repeated assessments of multiple athletes during a short time period (Cormack, Newton, McGuigan, & Doyle, 2008; Gathercole, Sporer, Stellingwerff, & Sleivert, 2015a; Markovic, Dizdar, Jukic, & Cardinale, 2004). Numerous CMJ protocols have been used for the assessment of low-frequency fatigue. However, single-repetition protocols are likely to be more efficient than multiple jumps (Joyce & Lewindon, 2014).

2.3.1. Neuromuscular Fatigue in Team Sports

The countermovement jump is one of the most widely used tests to assess neuromuscular fatigue in team sports. A number of researchers have found CMJ to be an objective marker of fatigue following a single (Cormack, Newton, & McGuigan, 2008; Wehbe et al., 2015) or multitude of matches (Andersson et al., 2008; Cormack et al., 2013; Cormack, Newton, McGuigan, & Cormie, 2008; Duffield, Murphy, Snape, Minett, & Skein, 2012; McLean et al., 2010; Ronglan, Raastad, & Borgesen, 2006) across various team sports. Research by Cormack, Newton, and McGuigan (2008) quantified the acute and short-term NMF response following a single elite AF match. The study involved 22 professional AF players (mean \pm SD; age 23 ± 3 years; body mass 89.6 ± 7 kg; height 1.90 ± 0.1 m) from a single team during a preseason match. CMJ data were collected from a commercially available force plate (440 series, Fitness Technology, Adelaide, Australia) at seven time points, pre- (48- and 0- h) and post- (0-, 24-, 72-, 96- and 120-h) match. Following a standardised 2-min dynamic warm-up and practice CMJs (x 3), participants completed the main CMJ trial at precise time points at either side of competition (pre – between 15:00 and 15:30; post – between 18:30 and 18:50). Data were log-transformed and effect sizes (\pm 90% CI) and

percentage changes at each time point compared with 48- and 0-h pre-calculated. Substantial reductions in CMJ flight time were found from pre- to post (ES -0.89 ± 0.56 ; -3.6%) and 24-h post-match (ES -0.84 ± 0.56 ; -3.5%), respectively. Subsequent post-match responses (72- to 120-h post) in CMJ flight time were unclear (ES range -0.02 to -0.10). Similarly, comparisons between CMJ flight time 48-h pre and all post-match time points also varied (ES range -0.17 to -0.47). These findings suggest that, in response to an AF match, CMJ flight time is a sensitive measure for identifying NMF. However, after 48-h, CMJ flight time may not be the best parameter.

Wehbe et al. (2015) provided a comparison between a novel cycling sprint test versus traditional CMJ testing for monitoring NMF following AF match play. Twelve academy AF players (mean \pm SD; age 18 ± 1 years; body mass 75.3 ± 8 kg; height 1.85 ± 0.1 m) from a single team participated. Players were randomly assigned into two groups, with one group completing the cycling sprint test first, followed by the CMJ or vice versa. These tests were performed at various time points before (24- and 1-h pre) and after (1-, 24- and 48-h post) the pre-season intra-club trial match. Prior to assessment of NMF, players either completed a 2-min self-paced warm-up on the cycle ergometer (Wattbike Pro, UK) before the 2 x 6-sec maximal sprints, separated by one minute of self-paced recovery or a 2-min dynamic warm-up ahead of the CMJ protocol. CMJ data were collected on a commercially available portable force plate (Kistler, USA). In addition to traditional null hypothesis statistics (test [sprint vs CMJ] * time), Cohen effect sizes (\pm 90% CI) and percentage change were calculated at each time point compared with 1-h pre. Small, non-significant differences were found between cycle peak power and CMJ flight time ($P = 0.5$; $\eta^2 = 0.6$). However, substantial decreases were found in CMJ flight time between pre-match and 1-h (ES -0.45 ± 0.27 ; -1.85%), 24-h (ES -0.70 ± 0.39 ; -2.92%) and 48-h post-match (ES -0.54

± 0.33 ; -2.25%), respectively. These findings extend those earlier findings (Cormack, Newton, & McGuigan, 2008; McLean et al., 2010) reporting a substantial decrease in CMJ flight time immediately post-match, remaining compromised for up to 48 h. Although changes in cycle ergometer peak power data were shown to be reduced (up to 24 h post), these were not as definitive, suggesting that the dissimilarity between cycling and running-based actions may question the efficacy of such tests to measure NMF in team sports.

Andersson and colleagues (2008) explored the changes in neuromuscular function following a condensed period of soccer fixtures (two matches in four days). Data were collected from the same two elite female soccer teams, competing in two 90-min friendlies against each other, separated by 72-h. Following the initial match, players were randomly assigned to either an active ($n = 8$; mean $\pm SD$; age 23 ± 4 years; body mass 63.6 ± 7 kg; height 1.67 ± 0.1 m) or passive ($n = 9$; age 22 ± 3 years; body mass 65.0 ± 5 kg; height 1.67 ± 0.1 m) recovery group. On match day, baseline measures of neuromuscular function were taken (20-m sprint, CMJ & maximal isokinetic knee flexion/extension) following a 5-min low-intensity standardised warm-up (Yo-Yo intermittent endurance level 1). CMJ data were collected on a commercially available force plate (Newton, USA), with the best jump height (out of three) taken. The same tests were repeated immediately post-match (within 15-min), 5-, 21-, 27-, 45-, 51- and 69-h after the first match and immediately after the second match. Immediately following the first match, a significant reduction in CMJ performance was observed (mean $\pm SE$; $-4.4 \pm 0.8\%$; $P < 0.05$). Furthermore, irrespective of recovery group, CMJ performance remained compromised (different to baseline values; $P < 0.05$) following the initial match (+ 69 & + 74-h). Moreover, at all time points, no significant differences were found between the two groups,

irrespective of recovery modality. Unfortunately, the authors present most of this data in a figure, making in-depth interpretation of time-course changes difficult. Although this study presents data on women's soccer, it can be postulated that these findings can further support those cited above (Cormack, Newton, & McGuigan, 2008; Wehbe et al., 2015) and demonstrates the existence and time-course patterns of reduced neuromuscular function (up to 74 h post), which is attenuated by a second match.

In a similar study, Ronglan et al. (2006) investigated the time-course changes in NMF following a five-day training camp or condensed period of competition (three matches in three days). Participants were national team female handball players and participated in either the off-season training camp ($n = 7$; mean \pm *SD*; age 24 ± 2 years; body mass 72.0 ± 6 kg; height 1.79 ± 0.0 m) or in-season international tournament ($n = 8$; age 23 ± 2 years; body mass 71.2 ± 2 kg; height 1.76 ± 0.1 m). Immediately prior to and after training, participants completed a NMF test battery consisting of voluntary isokinetic knee extensions, a CMJ and 20-m sprint test, respectively. During the competition phase, isokinetic knee extensions were omitted from the testing protocol, due to time constraints. Although the authors provide a comprehensive outline of study design with reference to both training and competition structure, they fail to include any information pertaining to the warm-up protocols prior to assessment of NMF. All three NMF tests indicated a significant reduction in performance (range -2 to -8 %; $P < 0.05$) during the training camp, with the greatest reductions observed in CMJ height (mean \pm *SD*; -6.9 ± 1.3 %; $P < 0.01$) on the second (48-h) and third day (72-h), respectively. During competition (3 matches in 3-days), NMF was also significantly effected, as shown by the reductions in CMJ height (-6.7 ± 1.3 %; $P < 0.01$). Unfortunately, the authors present most of this data in figures, making in-depth interpretation of time-course changes of CMJ performance difficult. Collectively, the

studies of Andersson et al. (2008); Ronglan et al. (2006), have both shown that, following a condensed fixture period, NMF is significantly inhibited. It may be postulated that, as professional cricketers also regularly participate in condensed fixture periods, cricketers could also experience considerable NMF following these condensed periods.

Although previous authors have detailed NMF following extended periods of competition (detailed above), data pertaining to season-long NMF is lacking. Cormack and colleagues (2008) sought to examine weekly differences in NMF over an AF competitive season. Data were collected from 15 professional AF players (mean \pm *SD*; age 25 ± 2 years; body mass 88.0 ± 8 kg; height 1.87 ± 0.1 m) during a 22-match regular season. Baseline CMJ data were collected with players in a rested state, 36-h before the first match of the season and repeated on 20 occasions throughout the season on a commercially available force plate (400 series, Adelaide, Australia). The authors outlined a typical weekly training and match schedule, indicating that CMJ data were collected on the morning of day three (approximately 72- to 144-h post-match, match day dependant). Prior to the CMJ trial, participants completed a 2-min dynamic warm-up including practice CMJs. Data were log-transformed with effect sizes (\pm 90% CI) and percentage changes calculated compared with pre-test data. CMJ data (flight time:Contraction time [ratio]) were shown to be substantially lower than pre at 60% of the sample points. The magnitude of this change from the pre-test data ranged from unclear (ES 0.04 ± 0.29 ; 1.0 %) to substantial (ES -0.77 ± 0.81 ; -17.1 %) decreases. These findings suggest that, during a competitive AF season, CMJ (flight time:Contraction time) data indicated that neuromuscular function was compromised for 12 of the 20 data points (60%), suggesting incomplete recovery from both training

and competition. By using this data, practitioners may wish to manipulate training loads or rest to restore neuromuscular function.

Similarly, McLean et al. (2010) also examined the differences in NMF spanning a competitive season, controlling for different between-match length microcycles. Twelve professional rugby league players (mean \pm *SD*; age 24 ± 4 years; body mass 102 ± 8 kg; height 1.85 ± 0.1 m) from the same team, competing throughout a 26-week season, participated. Baseline CMJ was collected at the end of a pre-season taper period, with subsequent CMJ data collected during three experimental weeks (3, 7 & 18 of the season), consisting of 5, 7- or 9-days between-match periods. All CMJ data were collected on a commercially available force plate (400 series, Adelaide, Australia) at a standardised time prior to training (08:00 to 10:00). All testing protocols including the standardised dynamic 5-min warm-up and data collection timelines were comprehensively outlined. Test data were converted into a Z-score (individual score–individual average/individual *SD*) to eliminate individual variability. Traditional null hypothesis testing coupled with effect size statistics (Cohen’s *d*) were performed. The results show that baseline CMJ data were significantly higher than the 24-h post-match value (ES = 1.67; $P < 0.01$) and the day before the next match at the end of the training microcycle (ES = 1.12; $P < 0.05$). Furthermore, the 24-h post-match CMJ values were also significantly lower than day-4 (ES = -1.06; $P < 0.01$) and the day before the next match at the end of the training microcycle (ES = 1.06; $P < 0.05$). These findings suggest that CMJ performance is reduced post-match, but returns to the highest in-season values 4-days post-match (~96-h). This new 96-h (4-day) window extends on the current understanding of incubation period of NMF outlined earlier (Andersson et al., 2008; Cormack, Newton, & McGuigan, 2008; Wehbe et al., 2015).

In addition to reductions in NMF following match play, research (Gathercole et al., 2015b; R. D. Johnston, Gabbett, Seibold, & Jenkins, 2014; Thorlund, Michalsik, Madsen, & Aagaard, 2008) has also explored the influence of simulated training/competition on neuromuscular function. Research conducted by Gathercole et al. (2015b) examined the capacity of four different field tests (squat- [SJ], depth- [DJ], countermovement-jump [CMJ] and 20-m sprint) to determine the sensitivity of NMF at various time points (0-, 24- & 72-h post, respectively). Data were collected from collegiate team sport athletes ($n = 8$; mean \pm *SD*; age 23 ± 4 years; body mass 80.6 ± 6 kg; height 1.84 ± 0.1 m). Testing protocols were strictly controlled with participants visiting at the same time of day, consuming the same meal at the same time, prior to each visit. Prior to testing, participants also completed a 20-min standardised warm-up (light jogging, dynamic stretching, 5 x 10 & 20-m sprints). Participants completed six trials of all jump protocols (SJ, DJ & CMJ) on a force plate (400 Series, Fitness Technology, Adelaide, Australia; sampling at 200 Hz) with a 1.5-min rest between jumps and a 5-min rest between tests. To administer a fatigue load similar to team sport activities, participants completed a 3-stage Yo-Yo protocol (Yo-Yo intermittent recovery level 2 & Yo-Yo intermittent endurance level 2 tests). All jump protocols were subsequently repeated at the three time points (0, 24, 72 h post) to assess fatigue sensitivity. Post-exercise log-transformed test data identified that wide-spread decreases were evident in CMJ performance. Specifically, at 0 h post fatiguing protocol, moderate reductions were observed in both flight time (mean effect size \pm 90% CI; 1.4 ± 2.8) and jump height (1.1 ± 1.2), respectively. By 24 h post fatiguing protocol, moderate reductions were still apparent in flight time (1.6 ± 1.7), with small reductions observed in jump height (0.5 ± 1.0). Whereas, 72 h post, only small reductions were found in flight time (0.5 ± 2.1) and jump height (0.7 ± 1.5),

respectively. The results show that a CMJ can offer an enhanced capacity to detect neuromuscular changes (up to 72-h post) compared to tests similar in nature.

Thorlund et al. (2008) identified the acute neuromuscular response following a simulated handball match. Data were collected from elite European handball players ($n = 10$; mean \pm *SD*; age 23 ± 2 years; body mass 91.7 ± 3 kg; height 1.88 ± 0.2 m) during a single simulated match. Pre-test (pre-simulation) participants performed 10-min general warm-up (cycle ergometer at 180 W) before completing a self-selected warm-up. Three maximal CMJs were performed with 30-45 s rest between each jump on a commercially available force plate (Kistler, USA), with the highest jump taken. The same CMJ test was completed immediately post-simulation (no warm-up was performed). The simulation consisted of seven series of multidirectional handball movements lasting 7-min, as outlined previously (Michalsik, 2004). Post-match jump height was significantly reduced (5.2%; $P < 0.01$).

R. D. Johnston et al. (2014) identified the role of contact, incorporated into specific training drills (small-sided games [SSG]) on NMF. Data were collected from a junior elite rugby league team ($n = 23$; mean \pm *SD*; age 19 ± 1 years; body mass 93.7 ± 9 kg; height 1.78 ± 0.2 m) with participants randomly assigned into groups. Within each group, players completed two separate training sessions. Group one completed training with a non-contact SSG on day one, before playing a SSG with contact 72-h later (group two completed this in reverse order). Each SSG consisted of two eight-minute halves (separated by 90 seconds rest) on a standardised grass playing area (30 m x 70 m). Neuromuscular function was assessed immediately before, immediately after, 12- and 24-h post SSG, using both a CMJ and plyometric press-up on a commercially available force plate (Kistler, USA). Irrespective of group, immediately post training, a significant reduction ($P = 0.001$) in CMJ peak power was observed.

Furthermore, moderate to large reductions were found immediately post training in CMJ power after the contact (mean \pm 95% CI; -0.88 ± 0.82 ES) and non-contact (-1.42 ± 0.93 ES) game, respectively. Reductions in CMJ power peaked at 12-h in both games (contact -1.40 ± 1.0 ES; non-contact -2.25 ± 1.1 ES), with small (contact -0.35 ± 0.63 ES) to moderate (non-contact -1.13 ± 0.91 ES), reductions still apparent at 24-h post training. These findings show reductions in lower body function as a result of both contact and non-contact SSGs. Moreover, these reductions were attenuated in the non-contact games, where it has been postulated that this is due to the increased running loads associated with non-contact training. As such, practitioners should consider the running demands of training prior to competition, ensuring that muscle function is not compromised.

Recently, the importance of high-speed running and accelerometry have been shown to be useful measures of exercise intensity and overall team performance, distinguishing between playing standard (Mohr, Krstrup, & Bangsbo, 2003; Mooney et al., 2013; Mooney et al., 2011). In light of this, researchers (Cormack et al., 2013; Duffield et al., 2012; Mooney et al., 2013; Thorpe et al., 2015) have started to explore the relationships between NMF and match performance, postulating that NMF will effect match intensity (assessed via high-speed running and accelerometry data). Early research (Duffield et al., 2012) explored the relationships between changes in NMF and the match demands of rugby league. Data were collected from eleven well-trained university rugby league players (mean \pm SD; age 20 ± 2 years; body mass 83.5 ± 11 kg; height 1.79 ± 0.1 m), classified as either playing in the backline ($n = 7$) or second row ($n = 4$). Match demands were collected from two to three competitive matches using a MEMS device (1 Hz GPS; GPSports, Canberra, Australia). NMF were

assessed using a linear force transducer (BMS, Fitness Technologies, Australia) providing CMJ height data at three time points adjacent to competition (pre, post and 2-h post-match). Prior to each CMJ (excluding post-match), participants completed a 5-min cycling warm-up (80 rpm with 2 kp resistance, Monark, Sweden and 3 practice jumps). Immediately post-match, a significant reduction in CMJ height was observed (mean \pm SD; -4.8 ± 12.1 %; $P < 0.05$), however at 2 h post no significant reduction was observed (-0.9 ± 16.1 %; $P < 0.05$). A total of 30 GPS data files were analysed and correlation analysis failed to show any relationships between match performance characteristics (e.g. high-speed running) and percentage change in CMJ following match play ($r < 0.25$). Although these findings agree with earlier research that NMF is compromised immediately following competition, it is important to acknowledge that this study used amateur players and may partly explain the post-match suppression of NMF, as match demands are lower. Furthermore, this study used 1 Hz GPS to record match data and, although the error of measurement is acceptable for total distance (TEM < 5 %), the reliability is questionable, specifically at high-speed velocities.

Mooney et al. (2013) also explored the relationships between NMF and match demands assessed via MEMS technology. However, in addition to GPS, the authors included accelerometry data, which has been shown to be more sensitive to subtle changes in movements than GPS. Data were collected from 17 professional AF players (mean \pm SD; 22 ± 3 years; body mass 86.5 ± 9 kg; height 1.88 ± 0.1 m) during a 22-match regular season. CMJ data (flight time:contact time ratio) were collected before the start of the season, with players in a rested state. Subsequently, CMJ data was collected weekly, a minimum of 96 h post-match (day after a day off) at the same time of day (09:00 – 10:00), allowing enough time for players to return to baseline values

(Cormack, Newton, & McGuigan, 2008). Following a 2-min standardised dynamic warm-up, participants completed the CMJ trial on a commercially available force plate (400 series, Adelaide, Australia). Subsequently, based on CMJ data, participants were categorised as either being fatigued or in a normal state. Match demands were collected using a MEMS device (5 Hz GPS and 100 Hz accelerometry; Catapult, Australia) and variables (total distance [m], high-intensity running [HIR > 15 km·h⁻¹] distance [m] & PlayerLoad™ [AU]) normalised to playing time (·min⁻¹). Data were analysed dependant on fatigue classification, with isolated interaction correlation analysis ($\pm 90\%$ CI). The results from this study identified meaningful changes in the relationship between PlayerLoad™·min⁻¹ and HIR·min⁻¹ ($\Delta r = 0.43 \pm 0.29$) and not between PlayerLoad™·min⁻¹ and m·min⁻¹ ($r = 0.18 \pm 0.27$) when players were in a fatigued state.

In a similar study using the same AF players, Cormack et al. (2013) also investigated the influence of NMF on accelerometry and running activity (assessed via MEMS) during a 22-match regular season. CMJ data (flight time:contact time ratio) were collected on a commercially available force plate (400 series, Adelaide, Australia) before the start of the season and then weekly, with a minimum of 96-h and up to 120-h post-match, allowing enough time for players to return to baseline values (Cormack, Newton, & McGuigan, 2008). Again, players were classified (using the same criteria) as either fatigued or non-fatigued and match demands recorded using a MEMS device (Catapult, Australia). Similar movement data were selected (total distance [m], high-intensity running [HIR > 15 km·h⁻¹] distance [m] & PlayerLoad™ [AU]) normalised to playing time (·min⁻¹), with the addition of accelerometer data in each individual vector (*x*, *y* and *z*). Data were log-transformed and the percentage difference ($\pm 90\%$ CI) comparisons made between fatigued and non-fatigued states.

This study identified that, when players were in a fatigued state, the largest percentage change ($-5.8 \pm 6.1 \%$) was observed in the vertical vector (z). This degree in reduction in the vertical vector was also apparent in $\text{PlayerLoad}^{\text{TM}} \cdot \text{min}^{-1}$ ($-5.1 \pm 4.7 \%$), $\text{HIR} \cdot \text{min}^{-1}$ ($-5.7 \pm 6.2 \%$) and $\text{m} \cdot \text{min}^{-1}$ ($-6.0 \pm 6.2 \%$) when adjusted to playing time, respectively. Ultimately, these findings demonstrate that NMF impacts on the movement characteristics in AF players, specifically in the vertical acceleration component (z), even when including HIR and total distance covered normalised to playing time ($\cdot \text{min}^{-1}$). Collectively, these studies suggest that NMF can be influenced by match intensity ($\text{m} \cdot \text{min}^{-1}$ & $\text{HIR} \cdot \text{min}^{-1}$), which has been shown to be an important factor in determining match outcome and success (Mohr et al., 2003; Mooney et al., 2013; Mooney et al., 2011).

Recently, Thorpe and colleagues (2015) quantified the relationships between daily training load and fatigue measures during a short 17-day in-season soccer training period. Data were collected from 10 outfield soccer players (mean \pm SD; 19 ± 1 years; body mass 75.4 ± 8 kg; height 1.84 ± 0.1 m) who were involved in normal team training ($n = 2$ reserve team matches; $n = 12$ straining sessions; $n = 3$ rest days). Individual daily training load data were collected using a MEMS device (5 Hz GPS; GPSports, Canberra, Australia), with total high-intensity running distance (THIR) reported. Prior to assessment of NMF (via CMJ), participants completed a standardised 5-min cycling warm-up (130 W at 85 rpm). The CMJs were performed on a commercially available jump mat (Fusion Sport, Australia), with participants performing two practice jump before the highest jump (out of 3) taken. Following partial correlation analysis ($\pm 95 \%$ CI), a small significant relationship between fluctuations in training load (THIR) and CMJ was found ($r = 0.23$ [0.04 to -0.41]; $P = 0.04$). Despite it being widely accepted that NMF assessed via a CMJ protocol is

compromised in the 72-h post-match, the results from this study challenge this. However, it is important to note that, both immediately post and 24-h post competition, players engaged in a rest day, thus preventing CMJ data being collected. Furthermore, THIR was employed as the only marker of training and match load and, again, should be questioned, as it has been shown to underestimate the true load in soccer, as it fails to distinguish between non-locomotive movement patterns (e.g. jumping, tacking kicking).

2.3.2. Neuromuscular Fatigue within Fast Bowling

In light of the aforementioned extensive use of CMJ protocols to measure NMF in response to competition and training, it would be expected that this data would be useful in cricket, specifically to monitor fast bowlers. Although some authors have described acute NMF in cricket (Duffield et al., 2009; McNamara et al., 2013; Minett et al., 2012a, 2012b), this is typically more as a secondary measure, with the main emphasis on changes in bowling performance.

To date, McNamara and colleagues (2013) are the only researchers to provide data pertaining to the fatigue responses of cricketers to competition and training. Data were collected from 26 state level academy cricketers (mean \pm SD; 18 \pm 1 years), categorised as either fast bowlers ($n = 9$) or other players ($n = 17$). Players were involved in a 7-week physical preparation period and a 10-day intensified competition period (3 x 50-over; 2 x 2-day; 2 x T20 matches). Player movements were recorded using a MEMS device (10 Hz GPS; 100 Hz accelerometer, Catapult, Melbourne, Australia) during both training ($n = 83$ data files) and competition ($n = 170$ data files), respectively. Prior to assessment of NMF (via CMJ), participants completed a standardised warm-up. Baseline CMJ data (flight time and relative peak power) were

collected prior to competition or training performed on a commercially-available force plate (Kistler, Switzerland). However, the authors failed to outline details of type and duration of warm-up and the time periods associated with CMJ data collection prior to competition/training, thus inhibiting comparisons with existing literature. All CMJ data were converted into a Z-score as outlined previously (McLean et al., 2010) and subsequently log-transformed for calculations of Cohen's (d) effect size ($\pm 90\%$ CI). Unclear differences were found in CMJ flight time between the fast bowling and non-fast bowling group in both the physical-preparation ($d = 0.34 \pm 0.47$) and competition phase ($d = 0.02 \pm 0.23$), respectively. Although unclear differences were reported, it may be suggested that, as the sample were junior academy cricketers, the overall physical demands may have been reduced, when compared to those made on adult professional cricketers. This is evident in the competition period, where they engaged in 2-day matches, not typically experienced by professional adult cricketers. Moreover, during this period of competition, although the authors present some external training load data (obtained from MEMS), they failed to present any information pertaining to descriptive fast bowling workloads (overs/balls bowled). It is therefore possible that these fast bowling loads are less than what may be typically expected during competition, resulting in a failure to induce notable physiological responses, thereby resulting in compromised CMJ performance. Finally, it is possible that if data analysis were performed within-groups and CMJ data were collected immediately post competition/training, differences in NMF might be found, especially as the external training load data (distance covered, high-speed running and accelerometry) identified that fast bowlers consistently performed at greater intensities.

In response to the potential issue related to acute NMF (pre > post measures), research conducted by Duffield et al. (2009) investigated the physiological responses to repeated spells of fast bowling (2 x 6-overs). Data were collected from six first-class professional fast bowlers (mean \pm SD; 23 \pm 3 years; body mass 86.9 \pm 11 kg; height 1.85 \pm 0.1 m) during the pre-competition phase. After a comprehensive familiarisation session, participants were then required to complete the testing session consisting of bowling two spells of the CA-AIS fast bowling skills test (2 x 6-overs, separated by 45-min walking). Player movements were recorded using a MEMS device (1 Hz GPS; GPSports, Australia) for the duration of the test. NMF were assessed before and after each spell by performing 5 x maximal vertical jumps as assessed for peak power and jump height using a secured force encoder (Gymaware, Australia). The differences in vertical jump height were determined between the respective 6-over spells, with Cohen's effect sizes (d) calculated. Analysis of vertical jump height identified small, non-significant differences ($P = 0.6$; $d < 0.2$) between the start and finish of spells or between pre to post in spell one (mean \pm SD; 0.43 \pm 0.06 vs 0.44 \pm 0.07 m) and spell two (0.42 \pm 0.07 vs 0.43 \pm 0.07 m), respectively. Interestingly, two 6-over spells of simulated fast bowling failed to elicit significant NMF. These findings are in agreement with McNamara et al. (2013), but conflict with data from other team sport simulations (Gathercole et al., 2015b; R. D. Johnston et al., 2014; Thorlund et al., 2008). One possible explanation for this is that this protocol is not capable of replicating match demands and therefore further analysis is warranted during competition. Collectively, these studies tend to suggest that collecting CMJ data was limited in identifying NMF. However, it is worth noting that this may be due to the low sample size, resulting in underpowered data. Furthermore, although some studies prescribed fast bowling loads (Duffield et al., 2009; Minett et al., 2012a,

2012b), fast bowlers may already be conditioned to bowling such loads (6-overs) and thus, a spell of this duration is not sufficient in administering notable NMF. Therefore, it may be proposed that by measuring a combination of neuromuscular, endocrine and perceptual markers, the identification of fatigue in cricket may be facilitated.

2.3.3. Validity and Reliability of Countermovement Jump (CMJ) Protocols

Despite the widespread use of CMJ, protocols data pertaining to their validity and reliability remains limited. Data from the same research group (Gathercole et al., 2015a, 2015b) examined the between- (day 1 vs day 3 vs day 5) and within-day (6 jumps) repeatability of either jumping and sprint tests (squat- [SJ], depth- [DJ], countermovement-jump [CMJ] and 20-m sprint) or 6-individual CMJ tests, respectively. Data were collected from the collegiate team sport athletes ($n = 11$; mean \pm *SD*; age 24 ± 4 years; body mass 80.6 ± 6 kg; height 1.82 ± 0.1 m). Following strict pre-exercise protocols and a 20-min standardised warm-up, participants completed all jumping protocols (as detailed in Section 2.3.1.). Data from Gathercole et al. (2015b) identified that overall high levels of repeatability were found in CMJ data (mean % *CV* \pm *SD*; 3.01 ± 1.1). Moreover, data from their other study (Gathercole et al., 2015a) demonstrated highly consistent values in both flight time (s) and jump height (m) both between- (mean % *CV* \pm *SD*; 1.1 ± 0.4 s; 4.9 ± 2.4 m) and within-day (1.7 ± 0.8 s; 5.3 ± 3.6 m), respectively.

Similarly, Cormack, Newton, McGuigan, and Doyle (2008) also explored the between- (day 1 vs day 2) and within-day (AM vs PM) repeatability of CMJ tests (1 x CMJ & 5 x CMJ). Data were collected from elite Australian football players ($n = 15$; mean \pm *SD*; age 23 ± 4 years; body mass 93.1 ± 8 kg; height 1.91 ± 0.1 m). Although testing protocols were well controlled, participants only completed a short (2-min)

dynamic warm-up prior to completing either CMJ protocol on a force plate (400 series, Adelaide, Australia; 200 Hz). Between- and within-day reliability of each force plate variable was calculated to determine typical error (*TE*) and coefficient of variation (% CV). Results show that between-day, highly reliable data were observed in both flight time (s) ($TE \pm 90\% \text{ CI}$; 0.02 [0.02 to 0.3]; % CV 3.3) and jump height (m) (0.02 [0.02 to 0.3]; % CV 5.0), respectively. Within-day, the same highly reliable trends were found for both flight time (0.02 [0.01 to 0.3]; % CV 2.9) and jump height (0.02 [0.02 to 0.4]; % CV 5.2). These studies along with earlier findings (Arteaga, Dorado, & Calbet, 2000; Markovic et al., 2004; Ronglan et al., 2006) and, more recently, (McNamara et al., 2013; Minett et al., 2012a; Wehbe et al., 2015), suggest that typical CMJ data (flight time and jump height) offer a highly acceptable level of reliability (% CV \approx 5) both within- and between-days, respectively. Therefore, practitioners and researchers can be confident that changes in CMJ data are elicited by fatigue and not measurement error.

2.4. Biochemical Markers of Fatigue

Professional athletes are frequently exposed to exhausting training and competition, which may temporally impair an athlete's performance (Bahnert, Norton, & Lock, 2012; Barnett, 2006). This impairment may be transitory, lasting minutes or hours following training or competition or may extend to several days (Barnett, 2006; Cormack, Newton, & McGuigan, 2008; Komi, 2000). In addition to changes in muscular performance due to fatigue (see Section 2.3.), short-term impairments result from metabolic disturbances, with long-term impairments related to exercise-induced muscle damage (EIMD) (Barnett, 2006). Exercise-induced muscle damage is a common occurrence following activities with a high eccentric component such as

prolonged, intermittent shuttle running (Twist & Eston, 2005). Furthermore, as fast bowlers are also exposed to repeated, eccentric muscle contraction forces during the fast bowling action, this may also result in EIMD (Noakes & Durandt, 2000). Exercise-induced muscle damage can result in muscle soreness, decreased range of motion, swelling and functional performance decrements (Hunkin, Fahrner, & Gatin, 2014; Twist & Eston, 2005). These symptoms may also compromise the quality of a player's subsequent performance in training or competition, which may be amplified further during periods of condensed scheduling (Oxendale, Twist, Daniels, & Highton, 2016), which are common in professional cricket.

Hormonal signals also play an important role in the repair and recovery mechanisms in men (Kraemer et al., 2009). The examination of endocrine measures associated with physical exercise have been widely documented, specifically in reference to cortisol that varies in the opposite direction to testosterone, showing an imbalance between the anabolic and catabolic hormones depending on the exercise intensity and duration (Urhausen, Gabriel, & Kindermann, 1995). Testosterone and cortisol play important roles in muscle hypertrophy and protein and glycogen synthesis, respectively (Urhausen et al., 1995). Specifically, cortisol has been used as an acute and chronic marker of decreased protein synthesis and increased protein degradation during exercise (C. P. McLellan et al., 2011b). This has led to the suggestion that cortisol could possibly be useful in identifying the impact of training and competition as a reflection of the balance between anabolic and catabolic processes (Cormack, Newton, McGuigan, & Cormie, 2008).

Effective monitoring strategies require tracking of variables that are sensitive to the physiological changes that accompany the training load variables associated by cricket-specific exercise. Various hormones (cortisol) and muscle enzymes (CK, UA

and urea) found in blood and saliva have the potential to provide information pertaining to an athlete's adaptation to a training load, both immediately and longer-term (3 – 7 days) and are therefore useful for monitoring training and recovery (Joyce & Lewindon, 2014; A. Scott et al., 2016). In light of this, the purpose of this section of the literature review is to outline some of the common biochemical markers used to describe the immediate and time-course fatigue response to team sports, where possible referencing cricket fast bowling.

2.4.1 Creatine Kinase (CK)

Creatine kinase (CK) is a compact enzyme that is found in both cytosol and the mitochondria of the muscle, where energy demands are high (Baird, Graham, Baker, & Bickerstaff, 2012; A. Scott et al., 2016). Creatine kinase forms the core energy network known as the phosphocreatine (PCr) system (Baird et al., 2012). In this energy circuit, the cytosol isoenzymes are closely coupled with glycolysis, producing adenosine triphosphate (ATP) for muscle activity (Baird et al., 2012). The pattern of CK tends to mirror the mechanical-muscular strain of exercise in the preceding days, reacting to the intensity and volume of exercise (Urhausen & Kindermann, 2002). Plasma levels reflect total circulating CK, with post-exercise increases considered to be representative of CK release from damaged muscle tissue (Brancaccio, Maffulli, & Limongelli, 2007; Hunkin et al., 2014). As a result of EIMD, skeletal muscle cell structure is altered by increased membrane permeability and CK is released from the muscle cell into the plasma via the lymphatic system (Brancaccio et al., 2007; Hunkin et al., 2014; C. P. McLellan, D. I. Lovell, & G. C. Gass, 2011a). Therefore, an extensive discussion in the literature has been instigated regarding the importance of elevated CK concentrations as an early indicator of player fatigue and recovery status.

In most cases, where an isolated case of EIMD occurs, this does not appear to cause further problems. However, in team sport, where players regularly train and compete, plasma CK is regularly used as an indirect biomarker quantifying the extent of EIMD (Buchheit et al., 2013; Hunkin et al., 2014; M. J. Johnston et al., 2016; R. D. Johnston et al., 2014; A. Scott et al., 2016; Slattery, Wallace, Bentley, & Coutts, 2012).

In the case of CK kinetics following competition, these studies can be further categorised into an acute response following a single match (de Hoyo et al., 2016; Hoffman et al., 2002; McLellan et al., 2010; C. P. McLellan et al., 2011a, 2011b; Young, Hepner, & Robbins, 2012) or spanning multiple fixtures in a condensed period (Andersson et al., 2008; R. D. Johnston et al., 2013; Oxendale et al., 2016). Although increases in plasma CK have been found from pre competition values, the response to competition tends to vary, with it typically peaking close to 24-h and remaining significantly elevated at 48-h post-match, respectively (Andersson et al., 2008; Coelho, Morandi, Melo, & Silami-Garcia, 2011; de Hoyo et al., 2016; M. J. Johnston et al., 2016; R. D. Johnston et al., 2013; McLellan et al., 2010; C. P. McLellan et al., 2011a, 2011b; Oxendale et al., 2016). However, in some cases, this CK remains elevated for between 72 – 120-h (McLellan et al., 2010; C. P. McLellan et al., 2011a, 2011b). Therefore, it is of increasing importance to identify the relationships between CK and indicators of match performance. Ultimately, such data may contribute to the effectiveness of biochemical markers to support the training and decision processes associated with coaches and practitioners, respectively.

Scott and colleagues (2016) sought to explore the relationships between physical match performance and post-match CK concentrations. Data were collected from 15 outfield professional English Premier League (EPL) soccer players (mean \pm *SD*; 26 \pm 4 years; body mass 84 \pm 6 kg; height 1.80 \pm 0.6 m) spanning an entire 39-

week competitive season. Match performance data were collected using a semi-automated multi-camera tracking system (Prozone[®], Leeds, England) at all home league fixtures ($n = 18$). Capillary blood samples were collected 48-h post-match at a standardised time prior to training (09:00 – 10:00 h). Immediately after collection, capillary blood samples were analysed via spectrophotometry for CK (Reflotron, Roche, Mannheim, Germany). Correlation coefficients were calculated between post-match CK (48-h) and match performance outputs (obtained via Prozone[®]). The results from this study show there were no significant relationships between any indicator of match performance and CK concentration measured 48-h post-match. The observed CK concentrations 48-h post-match ($520 \pm 224 \mu\text{mol}\cdot\text{L}^{-1}$) are similar to what has been described previously (Coelho et al., 2011). However, it is important to acknowledge that the time-course pattern of CK typically peaks ~24-h post-match (Coelho et al., 2011; M. J. Johnston et al., 2016; R. D. Johnston et al., 2014; Lombard, Muir, & Mckune, 2012), thus questioning the effectiveness of study design, monitoring CK concentrations up to 48-h post-match. Furthermore, the authors also fail to detail the training/recovery strategies adopted, which may also influence post-match CK kinetics.

Similarly, de Hoyo et al. (2016) sought to explore relationships between typical MEMS parameters and changes in CK, with additional pre- post-match CK analysis. Data were collected from 15 professional soccer players (mean \pm SD; 18 ± 1 years; body mass 75.6 ± 7 kg; height 1.80 ± 0.0 m). Of these 15, seven played in the whole match (90-min) with the remaining eight playing half the match (45-min). Match performance data were collected using MEMS technology (10 Hz GPS; SPI-elite, GPSports, Canberra, Australia) adopting previously detailed movement speed classifications (Hill-Haas, Dawson, Coutts, & Rowsell, 2009). Plasma CK was again

assessed via spectrophotometry (Reflotron, Abbot Architect, Illinois, USA). Capillary blood samples were collected 2-h pre-, 0.5-, 24- and 48-h post-match, respectively. Plasma CK data were log-transformed due to their heteroscedasticity. Relative differences (\pm 90% CI) were used to assess differences between pre- to post-match data. Pearson's correlation analysis ($r \pm$ 90% CI) was used to assess relationships between MEMS parameters and changes in CK concentration. Unfortunately, there is no further detail pertaining to the treatment of the data in regard to whether both the 90- and 45-min groups had their data pooled. However, the results show substantial changes in blood CK from pre- to 0.5- (28.6 % [13.1 to 46.3]), 24- (43.4 % [16.1 to 77.0]), and 48-h (26.0 % [2.2 to 55.5]) post-match, respectively. Further analysis showed that, for those players who played the whole match (90-min), very high-speed distance covered ($> 21 \text{ km}\cdot\text{h}^{-1}$) showed large relationships with both $\Delta\text{CK_pre_24}$ (change in CK concentration from pre- to 24-h post-match [$r = 0.56$; -0.32 to 0.82]) and $\Delta\text{CK_pre_48}$ (change in CK concentration from pre- to 48-h post-match [$r = 0.54$; 0.20 to 0.77]), respectively. Moreover, $\Delta\text{CK_pre_48}$ showed large correlations with high-speed distance covered ($> 14 \text{ km}\cdot\text{h}^{-1}$ [$r = 0.50$; 0.07 to 0.75]) and high-speed distance covered ($> 18 \text{ km}\cdot\text{h}^{-1}$ [$r = 0.58$; 0.17 to 0.77]). Collectively, these findings suggest that, following a competitive soccer match, there is a substantial increase in the expression of plasma CK. Importantly, these findings also support the notion that activities with a high eccentric component (e.g. high-speed running activity $\geq 14 \text{ km}\cdot\text{h}^{-1}$) would be associated with larger alterations in CK concentrations, which is in agreement with other team sport literature (C. P. McLellan et al., 2011a; Young et al., 2012).

In a collection of studies, McLellan and colleagues (2010; 2011a, 2011b) sought to quantify and explore relationships between the biochemical (CK) and

endocrine (sCort; see Section 2.5.3.) responses associated with professional rugby league competition, assessed via MEMS technology (GPS-accelerometry). McLellan et al. (2010) examined player movement patterns (via GPS) independent of the pre, during and post-match CK response to a single rugby league match. Data were collected from 17 professional rugby league players (mean \pm SD; 19 ± 1 years; body mass 89.6 ± 16 kg; height 1.88 ± 0.0 m), who played a minimum of 30-min of match play, in each half (2 x 40-min.). Subjects were rested for 24-h prior to data collection. Whole blood samples were collected daily (between 15:30 – 16:30 h) at eight time-points either side of match play (24-h, 30-min pre-match and 30-min, 24-h, 48-, 72-, 96- and 120-h post-match). Player movements were measured using a MEMS system (5 Hz GPS; SPI-Pro, GPSports, Canberra, Australia), with blood plasma analysed for CK (Reflotron, Abbott Architect, Illinois, USA). Creatine kinase data were log-transformed to normalise the distribution. In addition to the analysis of pre to post CK, further statistical analysis was performed to explore the relationships (Pearson's [r] correlation) between peak CK concentrations and GPS variables. Significant increases were found in plasma CK immediately post-match (30-min; $P < 0.05$; 56%) with a further significant increase and peak measure found at 24-h post-match ($P < 0.05$; 91%). A progressive decrease in CK was maintained from 48- to 120-h post-match, yet, all were significantly elevated from pre-match values ($P < 0.05$). Total distance was not significantly correlated with plasma CK during the match ($r = 0.28$; $P > 0.05$). Interestingly, this was the first study to show that CK concentrations remained elevated for up to 120-h post-match. Although the authors include data selection criteria (≥ 30 -mins playing time in each half) and TMA data pertaining to match play, they fail to discuss the high-speed running component, which is surprising, as this variable has been attributed to increased EIMD. Furthermore, the quality of the

opposition is not detailed, which may contribute to the continued elevation of CK, as superior opposition tends to cover greater distances at higher velocities, again attributed to team success and EIMD. However, this study does provide a comprehensive weekly outline of training, specifically including post-match recovery strategies. It may be that these strategies could have altered typical CK time-course responses (i.e. too physically demanding).

In addition to their earlier work, C. P. McLellan et al. (2011a) explored relationships between the biochemical responses to intensity, frequency and magnitude of collisions (derived from accelerometry) associated with professional rugby league match play. Data were collected from a different set of professional rugby league players ($n = 17$; mean \pm SD; 24 ± 7 years; body mass 94.6 ± 27 kg; height 1.88 ± 0.2 m), using the same inclusion criteria. All data pertaining to the intensity, frequency and magnitude of collisions (measured in gravitational force) were collected using tri-axial accelerometry embedded within a MEMS system (100 Hz; SPI-Pro, GPSports, Canberra, Australia) and based on methods from rugby union (Cunniffe et al., 2009) and manufacturers' guidelines. Furthermore, collisions were coded into severity zones (1 to 6) based on the acceleration G force characteristics, with zone one indicating the lowest impact or velocity of collision. To aid with the understanding of this, the authors provide a table depicting these classifications coupled with detailed text descriptors. Following log-transformation of raw CK data, the same statistical analysis (1-way repeated measures ANOVA), was performed. Additionally, a Pearson's (r) correlation coefficient was performed to explore relationships between muscle damage and physical contact. The results show that plasma CK became significantly elevated from pre-match values at 30-min post ($P = 0.003$; 77%), peaking at 24-h ($P = 0.002$; 267%), remaining significantly elevated until 120-h ($P = 0.04$;

43%) post-match. Further analysis identified that, as the severity of impact increased, so did the relationship with plasma CK concentrations. Specifically, zone 4 impacts were significantly correlated with 30-min ($r = 0.63$; $P = 0.04$), and 24-h ($r = 0.63$; $P = 0.03$) post-match CK concentrations. Whereas, zone 5 and 6 were significantly correlated to increased muscle damage at 30-min (zone 5 $r = 0.63$; $P = 0.04$; zone 6 $r = 0.61$; $P = 0.04$), 24- (zone 5 $r = 0.74$; $P = 0.009$; zone 6 $r = 0.77$; $P = 0.005$), 48- (zone 5 $r = 0.59$; $P = 0.04$; zone 6 $r = 0.59$; $P = 0.04$), and 72-h (zone 5 $r = 0.55$; $P = 0.05$; zone 6 $r = 0.55$; $P = 0.05$), post-match, respectively. Importantly, this study was the first to show the time-course relationships between accelerometry-derived data (impact zones) and CK concentrations. Although speculative, these findings may be transferable to fast bowling, especially as accelerometry is now being utilised to quantify external training load in cricket (McNamara et al., 2015a, 2015b; McNamara et al., 2013).

Young et al. (2012) described the movement demands of AF, subsequently exploring the associations between the time-motion characteristics and post-match CK concentrations. Fifteen junior professional AF players were recruited (range 16 – 18 years) and assessed during a single match. Unfortunately, no additional player characteristics or match training load measures were reported and one participant was omitted due to abnormally high CK values. Capillary whole blood CK samples were collected 24-h post-match and assessed for CK (Reflotron, Roche Diagnostics, Grezacherstrasse, Switzerland). Competition demands were quantified using a MEMS device (5 Hz GPS; Catapult Innovations, Melbourne, Australia). As a result of the CK concentrations, participants were median split into two groups (high or low CK). Initially, simple significance testing with magnitude-based inferences (ES) were performed to explore differences between the two groups against TMA variables.

Subsequently, Pearson's [r] correlation coefficients were used to explore the group-specific relationships between TMA variables and muscle damage. The results show many moderate to very large significant differences between the two groups for CK ([U·L⁻¹] $P < 0.001$; ES = 3.23), total distance ([m] $P < 0.05$; ES = 1.62), running ([4.0 – 6.0 m·s⁻¹] $P < 0.01$; ES = 1.91), fast running ([6.0 – 7.0 m·s⁻¹] $P < 0.001$; ES = 3.23) and PlayerLoad™ ([AU] $P < 0.05$; ES = 1.62), respectively. Further analysis identified that many of the correlations in the high CK group were associated with positive relationships, whereas the low group displayed the opposite direction relationship. Specifically, running ($r = 0.59$) and sprinting ($r = 0.42$) were shown to have the highest correlations with the high CK group. Although a number of factors are likely to contribute to muscle damage, the results from this study suggest that high-speed running (4.0 – 7.0 m·s⁻¹) is most likely associated with elevated CK, which tends to agree with earlier findings (Jones et al., 2014; Slattery et al., 2012; Young et al., 2012). Furthermore, it is worth acknowledging that although significant differences and moderate to large relationships were found, the statistical analysis may be underpowered due to the low subject numbers in each group ($n = 7$).

Further relationships between EIMD markers and match-play characteristics of professional rugby league have been researched. However, uniquely Oxendale et al. (2016) investigated the influence of playing position. Data were collected from 17 professional rugby league players (mean \pm SD; 25 \pm 4 years; body mass 98.5 \pm 10 kg; height 1.84 \pm 0.1 m) over four competitive matches, totalling 28 individual performances ($n = 11$ backs; $n = 17$ forwards). Following a rest day, participants provided a baseline whole blood sample (09:00 h), which was subsequently assessed for CK activity (Reflotron, Boehringer Mannheim, Germany). The next day, players competed in a rugby league match where time-motion characteristics were recorded

using a MEMS device (10 Hz GPS; Catapult Innovations, Melbourne, Australia). Whole blood CK were collected and assessed at 12-, 36- and 60-h post-match, respectively. Changes in CK concentrations were assessed at each time point, reporting mean differences (\pm 90% ES) using traditional methods. Further statistical analysis was performed to explore relationships (Pearson's correlation [r]) between these differences and match demands. There were significant increases in CK concentrations at 12- (808 ± 169 U.L; $P < 0.05$) and 36- (525 ± 136 U.L; $P < 0.05$) hours post-match, returning to baseline at 60-hours, respectively. Significant correlations were found between CK concentrations and match running performance. Specifically, playing time ($r = 0.9$ [0.77 to 0.96]; $P < 0.05$), total distance covered ($r = 0.86$ [0.70 to 0.95]; $P < 0.05$) and high-intensity running ($r = 0.76$ [0.51 to 0.91]; $P < 0.05$) all showed the strongest relationships to CK. The data presented suggest that subsequent muscle damage after rugby league is significantly dependant on the physical demands experienced by players, specifically between playing time, total distance covered and to a lesser extent high-speed running (≥ 18 km·h⁻¹). These findings reaffirm earlier team sport research (Jones et al., 2014; Young et al., 2012) and have important considerations for fast bowlers, as they have been shown to cover the greatest distances of all playing positions at the greatest intensities (Hulin et al., 2014; J. A. Johnstone et al., 2014; Petersen et al., 2010; Petersen, Pyne, Portus, Karppinen, et al., 2009).

While elevated CK has been reported in contact team sports and soccer following competition, there is limited information available pertaining to the impact of cricket fast bowling on skeletal muscle-damage or blood CK concentrations. To date,

Lombard et al. (2012) and Minett et al. (2012a, 2012b) are the only authors to detail the CK response following a spell(s) of fast bowling.

Lombard et al. (2012) sought to quantify the effects of bowling a single spell of indoor fast bowling on indirect markers of muscle damage (CK). Data were collected from 10 professional fast bowlers (mean \pm SD; 22 \pm 1 years; body mass 87.3 \pm 13 kg; height 1.81 \pm 0.1 m) during the pre-season phase. Prior to the indoor bowling spell (day 4) participants visited the lab (day 1) and provided a capillary blood sample which was assessed for CK (Reflotron, Roche Diagnostics, Indianapolis, USA) and underwent a series of tests (body composition, muscle pain questionnaire, range of motion and maximal isometric strength testing) before being instructed to ensure rest, performing limited physical activity (day 2 and 3). The bowling spell (8-overs; day 4) was performed at a standardised time (08:00 – 11:30 h). Participants were required to bowl each over as per match intensity and stand for 3-min between each over. CK was determined, measured immediately prior to a standardised 15-min dynamic bowling warm-up, with one hour post bowling and again 24-h later. The differences in CK were analysed against each of the three time points (pre, 1- and 24-h post). Preliminary data analysis showed no significant difference ($P > 0.05$) between CK on day 1 and pre-bowling on day 4, indicating that players returned in a rested state. Subsequent analysis revealed significant differences and relative percentage increases in CK activity at 1-h ($P = 0.03$; 109%) and 24-h ($P = 0.04$; 77%) post bowling spell compared to baseline. These findings show that bowling an 8-over spell had some effect on indirect markers of muscle damage. Creatine kinase usually peaks 24-h post exercise. However, this alternation in CK activity began to return to near baseline 24-h post bowling. Although this study failed to include any simulated fielding, unlike other acute fast bowling studies (Duffield et al., 2009; Minett et al., 2012a, 2012b), these

findings have practical applications to sport scientists and those involved in coaching, indicating that prescribing a spell of 8-overs during an indoor pre-season net training session does not result in a reduction in subsequent performance.

Minett et al. (2012a, 2012b) sought to examine the physiological and performance effects of either cooling or pre-cooling on fast bowlers in the heat. In addition to the data outlined in previous sections, these studies also explored the CK response following simulated fast bowling spells in the heat. In both these studies, venous blood samples were drawn before and 30-min post bowling and subsequently analysed for CK using an enzymatic method and bichromatic technique. An additional 24-h post session one blood sample was taken and the time point subsequently analysed during the repeated spell study (Minett et al., 2012a). The results from both these studies show no significant differences between conditions from pre to post (Minett et al., 2012a; $P \geq 0.05$; Minett et al., 2012b; $P \geq 0.05$). However, it is important to acknowledge that, although the purpose of these studies was to investigate the differences between intervention groups on the biochemical responses to spells of fast bowling, when extrapolating the data from the figures and tables presented, both clearly show that CK becomes elevated in response to 6- or 10-over spells, respectively. Data from these studies (Lombard et al., 2012; Minett et al., 2012a, 2012b) show that a spell of fast bowling is sufficient to elevate indirect markers of muscle damage (CK). However, in the 24-h following the spell of fast bowling, the increase in CK becomes somewhat attenuated, dependant on the duration of bowling spell. Therefore, it may be suggested that a “dose-response” relationship could exist between fast bowling training loads and EIMD.

2.4.2. Uric Acid (UA) and Urea

Some authors have suggested that the concentration of nitrogenous waste in blood plasma, namely uric acid (UA) and urea may be used as a marker of muscle protein breakdown (Bangsbo, 1994; Gleeson, 2002; Kindermann, 1986), as imbalances in protein metabolic homeostasis are associated with tissue damage (Hoffman et al., 2002; Viru, 1987). Specifically, uric acid is related to the degradation of adenonucleotides, whereas urea is produced in the process of formation of ornithine from arginine after the introduction of ammonia (NH₃) groups into the urea cycle (Viru & Viru, 2001). The exercise-induced increased concentrations are indicative of enhanced protein catabolism and stimulated gluconeogenesis, resulting from higher training loads (Urhausen & Kindermann, 2002; Viru & Viru, 2001). Unfortunately, data pertaining to these suggestions in team sport environments is scarce.

In an early review paper, Bangsbo (1994) explored the energy demands of competitive soccer, providing a reference to the metabolic and biochemical parameters associated with soccer competition. Although this study fails to include subject characteristics, venous blood data were collected from six soccer players at 10 time points before (pre and post warm-up), during (15-, 30-, 45- [first half]; 45-, 60-, 75, 90-mins [second half]) and after competition (10-min post). Venous blood samples were analysed for uric acid concentrations. Unfortunately, this data is only presented in a figure (mean \pm SEM), which may be a result of the small sample size. Extrapolating the data from this figure shows that, following the warm-up, where plasma uric acid concentrations were not noticeably altered, uric acid rose drastically during the first half (45-min). This pattern was mimicked during the second (45-min) half. Although plasma uric acid peaked at the end of the 90-min match, it remained

elevated post-match (10-min), suggesting that soccer match play may result in degradation of muscle fibres and EIMD.

In addition to the CK response outlined previously (see Section 2.3.1.), Andersson et al. (2008) also quantified additional biochemical parameters associated with EIMD following two women's soccer matches. As previously discussed, data were analysed to identify differences in uric acid and urea concentrations at the five time points following competition (matches 1 & 2). Both blood markers increased significantly (UA 10.9 ± 2 %; urea 14.8 ± 2 %; $P < 0.05$) at the end of the match. Furthermore, uric acid and urea concentrations reached peak concentrations immediately after the first match, returning baseline at 21-h. Again, immediately following match two, uric acid and urea concentrations were significantly increased ($P < 0.05$), showing the potential application for identifying acute exercise stress.

Although not taken from a true sporting environment, research from Chevion and colleagues (2003) explored the plasma antioxidant status of soldiers to withstand strenuous exercise. Data were collected from 31 highly trained soldiers (mean \pm *SD*; 19 ± 1 years; body mass 80 ± 6 kg; height 1.81 ± 0.0 m) during a six-month, five-day a week training schedule. Specifically, participants were monitored over a two-week period, where they performed two high-paced individual marches carrying a 35 kg Bergen over mixed terrain of 50- and 80 km (\approx 10- & 20-h, respectively). Venous blood samples were collected immediately prior to and following each march and subsequently analysed for uric acid, an indirect marker of muscle damage (leakage of muscle proteins into plasma). Unfortunately, the authors fail to disclose specific data relating to the intensity of these matches, yet provide a detailed procedure for the blood analysis. Differences in the pre to post uric acid concentrations were performed for

both distances. Plasma uric acid was significantly increased during the 50 km (77 ± 3 vs 96 ± 3 mg.L; 25 %; $P < 0.01$) and 80 km (90 ± 5 vs 123 ± 4 mg.L; 37 %; $P < 0.01$) march, respectively. In this study, uric acid was used as a marker of oxidative stress and muscle damage and was shown to reflect the strenuous activity administered in the form of long distance weighted marches.

Collectively, these studies (Andersson et al., 2008; Bangsbo, 1994; Chevion et al., 2003) show an acute significant increase in post competition/event uric acid and urea concentrations, suggesting enhanced nucleotide cycle turnover and the breakdown of amino acids. Data from soccer competition tended to show that uric acid and urea return to baseline within 21-h post-match, suggesting that this normalisation may not be suitable when coupling this data with indicators of NMF, which is typically suppressed for up to 48-h. However, data from Chevion and co-workers (2003) identified that plasma uric acid remained elevated and did not reach a normal basal level in the two weeks between intense physical activity (marching), which was deemed to be a consequence of the intense physical nature of the daily training. These findings have important considerations for team sport athletes who regularly engage in physical training following intense competition. Furthermore, it has been suggested that the necessity for uric acid determination in training monitoring has not been fully established (Viru & Viru, 2001).

2.4.3. Salivary Cortisol (sCort.)

Cortisol is considered an important stress hormone acting antagonistically with testosterone to mediate catabolic activity, increasing protein degradation and decreasing protein synthesis in muscle cells (McLellan et al., 2010). The presence of

cortisol is suggested as an indicator of the endocrine systems response to exercise and psychological stress (Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008). The use of salivary cortisol (sCort) is now commonly reported in team sports, largely owing to its non-invasive nature (Buchheit et al., 2013; Haneishi et al., 2007; Hayes, Grace, Baker, & Sculthorpe, 2015; Joyce & Lewindon, 2014). As a result, elevated sCort may be indicative of symptoms associated with overreaching and reflects the inability to recover following training and competition (Joyce & Lewindon, 2014). Mimicking the pattern detailed previously (see Section 2.4.1. – 2.4.2.), the majority of sCort studies tend to collect data in parallel with neuromuscular and biochemical fatigue markers at the same time points, identifying the typical responses acutely, following competition (Cormack, Newton, & McGuigan, 2008; Haneishi et al., 2007), or chronically, spanning a competitive season (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010). Unlike the biochemical markers, sCort responds at a more accelerated rate, typically peaking immediately following completion or within 24-h post-match (Cormack, Newton, & McGuigan, 2008; Haneishi et al., 2007; McLellan et al., 2010; C. P. McLellan et al., 2011a, 2011b). Despite most authors showing that sCort peaks immediately following competition, some have shown a significant reduction post-match, prior to a delayed response of up to 96-h post-match (McLean et al., 2010).

In addition to the neuromuscular responses following an AF match (see Section 2.3.1.), Cormack, Newton, and McGuigan (2008) also explored the impact of an elite AF match on hormonal status, specifically sCort. Data were collected from a squad of 22 professional AF players, with saliva samples collected at 48- and 0-h pre match, 0-, 24-, 72-, 96- and 120-h post-match, respectively. All saliva samples were collected at a standardised time during the testing protocol. Salivary cortisol

concentrations were determined in duplicate by an enzyme-linked immunosorbent assay (Salimetrics, Pennsylvania, USA) using a microplate reader (SpectraMax 190, Molecular Devices, California, USA). Raw data were log-transformed and subsequently analysed using effect size statistics (\pm 90% CI). Immediately following competition, sCort increased (34.2%) substantially (ES = 2.34 ± 1.06) and remained substantially elevated (41.8%; ES = 2.78 ± 1.16) 24-h post-match. Unclear and substantial decreases were shown at 72- (4.4%; ES = 0.34 ± 1.30), 96- (-16.6%; ES = -1.44 ± 0.91) and 120-h (-9.3%; ES = -0.78 ± 0.43) post-match, respectively. Salivary cortisol showed a clear pattern in response to a single AF match (up to 24-h post-match), substantially decreasing to pre-match values after 96-h. This pattern has also been shown both the assessment of NMF and indirect markers of muscle damage. Unfortunately, this study fails to provide any internal or external training load data pertaining to the match. While it is likely that a single AF match is capable of disrupting normal diurnal cortisol balance, these findings may not be a true reflection of the endocrine responses, as they fail to account for match intensity.

Similarly, Cormack and colleagues (2008) also examined weekly the hormonal status of professional AF players over a competitive season, exploring relationships between performance. Data were collected from 15 professional AF players, during a regular 22-match season. The authors outline a typical weekly training and competition schedule, detailing when saliva samples were collected (morning of Day 3; ~ 72- to 144-h post-match). A baseline saliva sample was collected in a rested state 36-h before the opening match of the season (pre) and on 20 occasions throughout the season. Salivary cortisol was determined using a previously detailed microplate reader method (Cormack, Newton, & McGuigan, 2008). Raw data were log-transformed and subsequently analysed using effect size statistics (\pm 90% CI). Pearson's correlations

($r \pm 90\%$ CI) were also calculated to assess relationships of absolute values and percentage difference from pre-values. Saliva cortisol concentrations were substantially lower than the initial pre-competition value in all but one weekly comparisons (mean \pm SD 2.34 ± 0.62 $\mu\text{g}\cdot\text{dL}$; up to $-40 \pm 14.1\%$; ES -2.17 ± 0.56) except mid-week 1 – 2, where the response was trivial ($-6.1 \pm 9.7\%$; ES -0.27 ± 0.39). A possible explanation for trivial reduction in sCort associated with mid-week 1 – 2 may be that this was the only saliva sample to be taken 144-h post-match, whereas all other samples were typically taken between 72- and 96-h post-match. Furthermore, a small correlation ($r = -0.16 \pm 0.1$) was found between sCort and the number of coaches' votes, being an assessment by coaching staff on the effectiveness of a player's performance, based on their assigned role. The results from this study suggest that a competitive AF season elicits fluctuations in sCort. Moreover, the pattern seen in sCort suggests that, between 72- and 96-h post-match, players were unlikely to be in a catabolic state as a result of competition or training loads. This finding is in agreement with both CK concentration and NMF responses following competition, where fatigue and markers of muscle damage typically subside after 48-h. Furthermore, sCort has a small relationship with performance, suggesting that it may be a useful variable for monitoring the response to AF training and competition.

As part of the comprehensive collection of biochemical studies, McLellan and colleagues (2010; 2011a, 2011b) also quantified the endocrine (sCort) response and its association with professional rugby league competition. McLellan et al. (2010) examined player movement patterns (via GPS) independent of the pre, during and post-match sCort response to a single rugby league match. Salivary cortisol was also collected during the same time points as detailed previously (see Section 2.4.1.). Unstimulated saliva was collected (via passive drool) prior to analysis in duplicate,

using an enzyme-linked immunosorbent assay on a microplate reader (SpectraMax 190, Molecular Devices, California, USA). Raw sCort data were log-transformed and differences in the mean calculated using traditional single repeated measures analysis of variance, with descriptive percentage differences. Furthermore, Pearson's product-moment correlations (r) were performed to explore the relationships between peak sCort concentrations and GPS variables. A significant increase, where sCort peaked, was found 30-min post-match ($P < 0.05$; 68%), with a further significant increase found at 24-h post-match ($P < 0.05$; 28%). Salivary cortisol returned to near baseline levels after 48-h post-match (-37%), remaining reduced for the remainder of the data collection period (up to 120-h). Total distance was not significantly correlated with sCort during the match ($r = 0.09$; $P > 0.05$). Interestingly, this is the first study to show a significant reduction in sCort 96-h post-match.

McLellan and co-workers (2011b) also examined the sCort response following a single rugby league match. Salivary cortisol was collected and analysed during the same time points, using the same equipment as previously described (McLellan et al., 2010). Salivary cortisol was significantly elevated post-match (30-min; $P = 0.001$; 117%) remaining elevated at 24-h post-match ($P \leq 0.01$; 51%), respectively. Finally, significant reductions in sCort were found 96-h ($P = 0.042$; -30%) post-match. These findings of increased sCort immediately and 24-h following competition are consistent with their previous work and that of others (Cormack, Newton, & McGuigan, 2008; Haneishi et al., 2007; Hoffman et al., 2002; McLellan et al., 2010). Interestingly, this also identified a reduction in sCort 96-h following competition, supporting their earlier work (McLellan et al., 2010), and may be a result of a reduction in psychological anticipation, as previously mentioned (P Passelergue & Lac, 1999).

Christopher P McLellan, Dale I Lovell, and Gregory C Gass (2011) also explored the relationship between sCort and physical impacts, utilising MEMS technology. All research methodology pertaining to sCort collection, analysis and data analysis followed their earlier study design (McLellan et al., 2010; C. P. McLellan et al., 2011b). The results show that sCort became significantly elevated at 30-min ($P = 0.001$; 117%) and 24-h ($P = 0.001$; 51%) post-match, respectively. Again, like their earlier work, sCort was significantly reduced to below baseline values at 96-h ($P < 0.05$; -30%) post-match. Despite significant increases in sCort following competition and unlike the significant relationships observed with CK and physical impact, there were no significant correlations with sCort and impact. The peak concentrations of sCort post-match (30-min) and subsequently returning to near baseline after 24- to 48-h following competition are consistent with others and their earlier work (Cormack, Newton, & McGuigan, 2008; Haneishi et al., 2007; Hoffman et al., 2002; McLellan et al., 2010; C. P. McLellan et al., 2011b), thus indicating a recovery period where homeostasis is resumed and the removal of match-related psychological and physical stressors occur within 48-h (McLean et al., 2010; P Passelergue & Lac, 1999).

Similarly, McLean et al. (2010) also examined changes in NMF (see Section 2.3.1.) and hormonal status, following rugby league matches over a competitive season, with reference to different between-match microcycles. Data were collected from 12 professional rugby league players, throughout a 26-week season. The season was split into three experimental weeks consisting of 5-, 7- and 9-days between-match periods. The three weekly training and competition schedules are subsequently detailed indicating the time periods of saliva collection (training 08:00 h; competition 11:00 h). All saliva samples were collected from players 4-h pre-match, 1-, 2- and 4-days post-match in each microcycle. Again, sCort concentrations were determined by

an enzyme-linked immunosorbent assay using a microplate reader (Cormack, Newton, & McGuigan, 2008). Raw data were converted to a Z-score to eliminate data variability and differences determined using null hypothesis testing with magnitude-based inferences (Cohen's *d*). As expected, due to the number of available training days, a higher overall training load was found in the 9-day when compared with the 5-day ($P < 0.001$; $d = 0.95$) and 7-day ($P < 0.001$; $d = 0.69$) microcycles and between the 7-day and 5-day ($P < 0.001$; $d = 0.81$) microcycle, respectively. The time-course changes in sCort over the three microcycles indicated that, on "Day 4", sCort was significantly higher than game day in the 9- and 7-day microcycles ($P < 0.01$; $d = 0.60$) and, although not significant, was higher than on "Day 1" following competition ($P < 0.07$; $d = 0.69$), respectively. The results from this study show that sCort is reduced for 24- to 48-h post-match and does not rise significantly until "Day 4" following competition. These current findings produce conflicting data to what has been previously found (Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; Haneishi et al., 2007), showing sCort to be elevated several days following competition.

Haneishi et al. (2007) conducted a relatively simple study comparing the stress response during a competitive soccer match and typical training session. Ten collegiate female soccer players (mean \pm *SD*; 20 ± 2 years; body mass 58.3 ± 7 kg; height 1.66 ± 0.7 m) provided four saliva samples; one pre-match (30-min) and one post-match (10-min) and one immediately before and one immediately after practice. Although the method provides a detailed description of the training session (timing and environmental conditions), unfortunately, competition data is somewhat lacking, with the match outcome (0 – 1) the only detail. Salivary cortisol concentrations were determined using an enzyme immunoassay (Diagnostic Systems Laboratories,

Tennessee, USA). Traditional null hypothesis analysis was performed on both pre-to-post sCort competition and training data. Following competition, sCort concentrations increased significantly (250%; $P \leq 0.05$), whereas, following training, no significant differences were found ($P > 0.05$). This data identifies the far greater stress hormone response following competition than what was experienced following training. Ultimately, by providing some training load data, this study would allow for far greater interpretation of the data.

To date, McNamara and colleagues (2013) are the only researchers to comprehensively examine both neuromuscular (see Section 2.3.2.) and endocrine responses of cricketers to competition and training. Data were collected from 26 state-level academy cricketers (mean \pm SD; 18 ± 1 years), categorised as either fast bowlers ($n = 9$) or other players ($n = 17$). Players were involved in a 7-week physical preparation period and a 10-day intensified competition period (3 x 50-over; 2 x 2-day; 2 x T20 matches). Salivary data (cortisol and testosterone) were collected using oral swabs (Salimetrics, State College, PA, USA) once a week during the physical-preparation phase ($n = 7$ Thursdays – 08:00 h) and every day during competition. The magnitude of differences (Cohen's effect size [d] with 90% CI) and percentage likelihood (\geq SWC) between bowlers and non-fast bowlers were performed. Over the physical-preparation period, salivary cortisol concentrations were greater in the fast bowling group ($d = -0.88 \pm 0.39$; 100%) than non-fast bowlers. Furthermore, cortisol concentrations during the competition period were greater in the fast bowling group ($d = -0.39 \pm 0.30$; 85%) than non-fast bowling group. These elevated cortisol concentrations shown across both periods are possibly linked to the increased training

loads of fast bowlers. However, it is important to acknowledge that this data is taken from professional academy cricketers and thus may differ from senior professionals.

2.4.4. Validity and Reliability of Biochemical Markers of Fatigue

Despite many biochemical measures being used as markers of training stress and fatigue, it is important to understand the possible limitations associated with these measures. In turn, this will allow for a more informed decision when considering these as markers to monitor EIMD and fatigue. Consequently, this section of the literature review will highlight the validity and reliability of both CK and sCort, owing to their widespread reporting within the literature and this thesis.

Creatine kinase (CK)

Exercise-induced muscle damage is a typical response to heavy training loads, resulting in an increase in CK (Brancaccio et al., 2007). Therefore, the quantification of EIMD by monitoring the degree of muscle damage using CK has attracted significant attention. However, many factors effect the large degree of variability to which CK increases during and after exercise.

The resting value of CK has been shown to range from 45-267 U/L (Kim & Lee, 2015), with a breakpoint identified at 300-500 U/L of CK release after exercise (Brancaccio et al., 2007), with peak values shown at over 10,000 U/L (Kim & Lee, 2015). This post-exercise CK activity depends on training status, with athletes possessing a higher resting value. These findings are attributed to a larger muscle mass and training adaptations, yet post-exercise, the peak value is lower than in untrained individuals (Vincent & Vincent, 1997). Interestingly, if athletes and sedentary individuals complete the same exercise test, CK concentrations of athletes are lower

than the matched healthy control group (Brancaccio et al., 2007; Karamizrak, Ergen, Töre, & Akgün, 1994). Consequently, the high variability of CK has allowed for individual responses to be classified into either high or low responders. Athletes who demonstrate chronically low CK values (low responders) have low variability in comparison with those who have higher values (high responders). Therefore, it has been suggested (Hartmann & Mester, 2000), that the significant detection of EIMD may be possible when combining large increases in CK with reductions in exercise tolerance. In conclusion, CK can be used to identify EIMD in athletes. However, large amounts of variability exist and this must be considered when interpreting results (Guilhem et al., 2015; McGuigan, 2017).

Salivary Cortisol (sCort)

Saliva collection and analysis has rapidly developed as a tool for the measurement and assessment of physiological biomarkers (Hayes et al., 2015). Saliva can be collected rapidly, frequently and without the associated stresses of venepuncture. Given its importance as a stress hormone, sCort has gathered increasing popularity as a marker in athlete monitoring (McGuigan, 2017) and is considered to be a true reflection of serum and plasma values (Fisher, McLellan, & Sinclair, 2016). Additionally, low sample volumes (0.5-2.0 mL) are typically sufficient to allow for an accurate saliva analysis, can be performed more frequently, rapidly and require less training than venepuncture, thus presenting an attractive athlete-friendly option for applied sport science research and practice (Fisher et al., 2016; Papacosta & Nassis, 2011).

Salivary Cortisol has previously been validated (Crewther, Lowe, Ingram, & Weatherby, 2010) against the corresponding blood measurement, with the authors identifying that in response to a short, high-intensity cycle bout, sCort was superior in

identifying changes to exercise. Furthermore, by monitoring the hormonal response to exercise, it can provide an accurate means of identifying excessive training fatigue or the onset of overreaching (Papacosta & Nassis, 2011). In conclusion, the assessment of sCort can provide a feasible and reliable tool for monitoring stress in sports and exercise, thus saliva collection and analysis has essential and significant practical applications (Fisher et al., 2016; Papacosta & Nassis, 2011).

2.5. Summary

- Monitoring of fast bowling work and training load has allowed for a greater understanding of the risk factors associated with cricket, especially amongst fast bowlers.
- As a consequence of its introduction, T20 cricket (2005/6) now presents a noteworthy challenge to sports medicine and sport science practitioners in terms of preparation strategies.
- Generally, it appears that a moderate bowling load is protective against injury, whereas too high or too low can increase the risk of injury.
- This is of increased importance when players engage in periods of limited overs cricket, specifically T20, where fast bowling workloads may not meet the upper and lower thresholds associated with injury risk.
- Fast bowlers cover the greatest distances of all playing positions.
- Aside from total distance, fast bowlers also covered the greatest distances in high-speed locomotive activities across all formats of competition.
- The technical error of measurement (TEM) of 5 Hz GPS during simulated team sport has been reported as;
 - TD = 2.0 %

- Low-speed (mean running speed $\leq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance = 4.3%
- High-speed (mean running speed $\geq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance = 10.8% (R. J. Johnston et al., 2012; Petersen, Pyne, Portus, & Dawson, 2009).
- The tri-axial accelerometer embedded within the MinimaxX devices has been reported to provide a highly reliable ($< 2\%$ CV) measure of PlayerLoad™ in both laboratory (Boyd et al., 2011) and team sport simulations (Barrett et al., 2015; R. J. Johnston et al., 2012).
- Countermovement jump tests offer a high level of practicality and reliability, while requiring minimal physiological strain.
- Neuromuscular function (assessed via CMJ) appears to be significantly effected for up to 48-h post-match.
- The measurement of biochemical, specifically (CK), and endocrine (sCort) measures in response to training and competition is now common place in team sports.
- CK provides an accurate indirect measure of EIMD, typically peaking 24-h post-match.
- sCort can be collected rapidly and frequently, providing a measure of psychological stress, typically peaking immediately after competition, but remaining present for up to 24-h.

3. General Methodologies

This chapter describes the general procedures that were conducted throughout each experimental chapter. The specific methodologies for each individual experiment are described where necessary.

Subjects

The subjects recruited for this thesis were male medium to fast bowlers aged between 17 and 35. Subjects were either (a) part-time senior club-level cricketers (Hunters ECB Yorkshire Premier League North) who reported \geq two training sessions and one competition day per week ($n = 11$; see Chapter 7) or (b) professional full-time cricketers from the same English County Cricket Club ($n = 14$; see Chapter 5 – 6, respectively). For the purpose of this thesis, a fast bowler was defined as a bowler from whom the wicket keeper would normally stand back from the stumps, due to bowling speed (Dennis et al., 2004; Dennis et al., 2003; Dennis et al., 2005). However, further bowling speed classifications were obtained from the open-access public website espncricinfo.com, specifically for the professional full-time cricketers. The Department of Sport, Health and Exercise Science Ethics Committee at the University of Hull approved all experimental procedures and the study conformed to the declaration of Helsinki (World Medical, 2013). Prior to undertaking the various experimental procedures, players were informed of all testing procedures and provided written informed consent. Furthermore, players followed a prescribed pre-match routine; no alcohol (24-h), avoiding caffeine (2-h), maintaining a well-rested and hydrated state. All players were free from injury or any other medical condition that would prohibit participation.

Anthropometric data

Body mass (kg) and height (cm) were measured using SECA digital scales (SECA, Birmingham, UK) and Holtain Stationmaster (Holtain Ltd, Crymych, Dyfed), respectively.

Competition playing surface

All matches were played on a professionally prepared first-class county cricket oval within the United Kingdom. The cricket oval conformed to and met the requirements of Law 7 (The Pitch) and Law 10 (Preparation and Maintenance of the Playing Area) of the Marylebone Cricket Club (MCC) Laws of Cricket (MCC, 2013).

Movement Characteristics

The movement characteristics of each fast bowler were recorded using a portable micro--electro-mechanical system (MEMS) device (MinimaxX Team Sports v2.5, Catapult Innovations, Melbourne, Australia; mass 64.5 g; size 0.9 x 0.5 x 0.2 cm) encased within a neoprene vest, which housed the device between the scapulae (Figure 3.1.). The MEMS device included a global positioning system (GPS) device sampling at 5 Hz and a tri-axial piezoelectric linear accelerometer (Kionix, KXP94) sampling at 100 Hz. As recommended, each bowler wore the same MEMS device throughout all testing procedures to avoid interunit error (Jennings et al., 2010b; R. J. Johnston, Watsford, Austin, Pine, & Spurrs, 2015; Petersen, Pyne, Portus, & Dawson, 2009). The measurement error (technical error of measurement [TEM]) in the MEMS devices used for total distance, low-speed (mean running speed $\leq 14.4 \text{ km}\cdot\text{h}^{-1}$) and high-speed (mean running speed $\geq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance during simulated team sport activities is reported to be 2.0%, 4.3% and 10.8%, respectively (R. J. Johnston et al.,

2012; Petersen, Pyne, Portus, & Dawson, 2009). Moreover, the tri-axial piezoelectric linear accelerometer embedded within the MEMS device has been reported to provide a highly reliable ($< 2.0\%$ CV) measure of PlayerLoad™ in both laboratory (Boyd et al., 2011) and team sport simulations (Barrett et al., 2015; R. J. Johnston et al., 2012).



Figure 3.1. Portable MEMS device (L) and fast bowler wearing a bespoke neoprene vest (R). The arrow indicates unit placement, between the scapulae within a custom-made pouch as part of the bespoke neoprene vest.

Approximately 30-min before use, the units were switched on to ensure either (a) that they were able to establish a satellite lock (≥ 4 satellites for ≥ 15 min; see Chapter 5 & 6) or (b) that the accelerometer was calibrated according to the manufacturer's instructions (see Chapter 7.). The units were switched off immediately after each trial.

Movement demands were quantified using total distance, which was further characterised into arbitrary speed zones and descriptors, in line with previous studies (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009) (see Table 3.1.). Furthermore, we also reclassified the speed zones into a broader range allowing for further comparisons with existing literature (Kempton, Sirotic, &

Coutts, 2014; Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015; McLaren, Weston, Smith, Cramb, & Portas, 2016). The zones included low-speed ($LSRD \leq 14.4 \text{ km}\cdot\text{h}^{-1}$) and high-speed ($HSRD \geq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance, respectively. High-speed locomotive efforts are reported with a dwell time of 0.2 s in an attempt to reduce errors that can occur in the smoothing of data used by the software (Petersen, Pyne, Portus, & Dawson, 2009). In addition to the GPS parameters, PlayerLoad™, expressed in arbitrary units (AU), was calculated in Sprint (Catapult Innovations, Melbourne, Australia). PlayerLoad™ is a modified vector magnitude expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each three vectors (X, Y and Z axis) and divided by 100 (Boyd et al., 2011) (see Chapter 2; Figure 2.6.).

Table 3.1. Movement Category Speeds, as reported by Petersen, Portus, et al. (2009); Petersen, Pyne, Portus, and Dawson (2009), and Petersen et al. (2010).

Movement classification	Speed ($\text{km}\cdot\text{h}^{-1}$)
Standing/Walking	0.0 – 7.2
Jogging	7.2 – 12.6
Running	12.6 – 14.4
Striding	14.4 – 18.0
Sprinting	>18.0

Following use, MEMS data were downloaded using Sprint software (V5.1.0, Catapult Innovations, Melbourne, Australia) and subsequently analysed and processed by applying the proprietary intelligent motion filter. Throughout all GPS data collection

periods, individual unit validity and reliability were identified by extrapolating the number of satellites that were found to be available for signal transmission using Catapult Sprint software (Sprint, Version 5.1.0, Catapult Innovations, Melbourne, Australia). The minimum satellite signal strength was set at ≥ 5 satellites, which is in line with that set by Jennings et al. (2010a); Waldron et al. (2011) for the optimal use of GPS technology for assessment of human movement. Furthermore, the mean horizontal dilution of precision (HDOP) was also extrapolated. A horizontal dilution of position of 1 indicates an optimal geometrical positioning of orbiting satellites for accurate monitoring of position, while larger values (up to 50) are considered to provide unreliable results (Jennings et al., 2010a; Waldron et al., 2011; Witte & Wilson, 2005). No data were omitted due to poor signal quality.

Cropping of data

Each experimental data file was subsequently split into specific reference periods, which were then used to construct performance profiles for their specific reference periods. To construct these specific match activity reference periods, each individual match file was split to account for bowling periods, which were determined through the use of the official match scorer and MEMS data (J. A. Johnstone et al., 2017).

An individual over was cropped, so that data obtained included the initial run-up of the first delivery and all subsequent movements and actions until cessation of the final delivery in the over (typically six deliveries). However, on occasion, as a result of an illegal delivery, the number of deliveries in “an over” would increase in line with the MCC Laws of Cricket (MCC, 2013). In every instance prior to the first delivery being bowled, the initial run-up was identified by viewing the GPS map in parallel with the accelerometer data (Figure 3.2.). Subsequently, a 10-sec period of

inactivity prior to the first delivery in the over and a period ending 10-sec after the last delivery in the over were adopted as inclusion/exclusion criteria and became self-defining (J. A. Johnstone et al., 2017). All external training load variables were represented in absolute and relative terms, indicative of volume and intensity, respectively. Relative measures were calculated as the absolute measure divided by the on-field playing time.

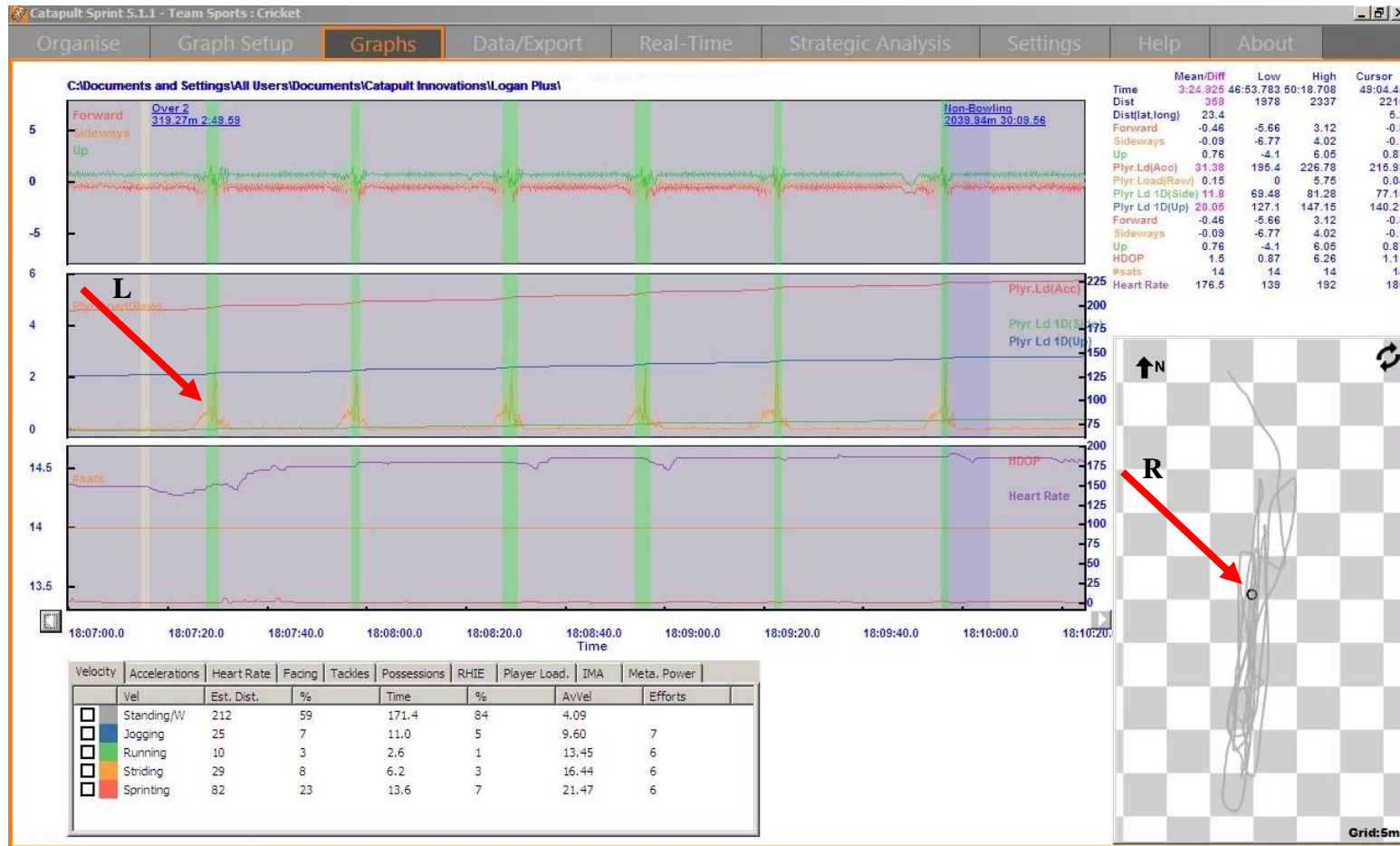


Figure 3.2. Screen-shot of Sprint software to highlight the cropping process. Arrow (L) indicates the raw accelerometer trace, with arrow (R) indicating the GPS map.

Warm-up

Prior to performing a vertical countermovement jump (CMJ) test, players completed a standardised 10-min dynamic warm-up protocol similar to that previously described, including dynamic stretches followed by a series of different running patterns progressively increasing in intensity (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010; McNamara et al., 2013) (see Appendix A).

Countermovement Jump

After completion of the standardised warm-up, players completed three submaximal practice CMJs prior to the measurement trial. Each player then performed three CMJs, with three minutes of rest between each CMJ. The CMJ was performed on a commercially available electronic jump mat (Smart Jump, Fusion Sport, Queensland, Australia) operated by manufacturer software (Smart Speed, Fusion Sport, Queensland, Australia) to calculate flight time (FT [ms]). All CMJs were performed with hands held firmly on the hips and subjects were instructed to jump as high as possible. All jumps were performed at a self-selected countermovement depth (Cormack, Newton, McGuigan, & Cormie, 2008; McNamara et al., 2013). In accordance with the methods outlined by Bosco, Komi, Tihanyi, Fekete, and Apor (1983), the highest vertical jump was used for data analysis.

Cricket Australia-Australian Institute of Sport (CA-AIS) fast-bowling skills test

In experiment three (Chapter 7.), players completed an adapted version of the Cricket Australia-Australian Institute of Sport (CA-AIS) fast-bowling skills test (Duffield et al., 2009; M. Portus et al., 2010) (Figure 3.3.). Before commencement, players completed a standardised warm-up (see Warm-up), followed by the CMJ test (see

Countermovement Jump). Players then performed 10 practice deliveries, gradually increasing bowling speed to match intensity. Players then performed a bowling spell based on the CA-AIS fast bowling skills test, whereby players aimed to bowl a randomised assortment of short-, good- and full-length deliveries on off-, and leg-stump lines at match intensity, to replicate skill-based match requirements. Bowling in pairs and alternating overs, players aimed at the stump lines as instructed, prior to bowling each delivery at the batsman's end. The order of delivery type was standardised for each bowler as per the 4-over CA-AIS fast bowling skills test. The same 4-over order was replicated to extend the bowling spell to meet the over requirements of each experimental trial. Total run-up and final 5 m run-up speeds were recorded with a wireless infra-red timing system (Brower Timing Systems, Draper, USA). Each bowling spell was completed using a new regulation four-piece (156 g) cricket ball (County Supreme A, Readers, Northamptonshire, UK). Between overs, players completed physical activities to simulate match demands, including walking 10 m as each ball was delivered by their bowling partner and a 20 m sprint on the 2nd and 4th ball of each over. The four different bowling spells (4-, 6-, 10-overs and a random number of deliveries [between 36 and 60 balls]) were selected to simulate typical bowling spells encountered in professional limited overs cricket (Chapter 7.).

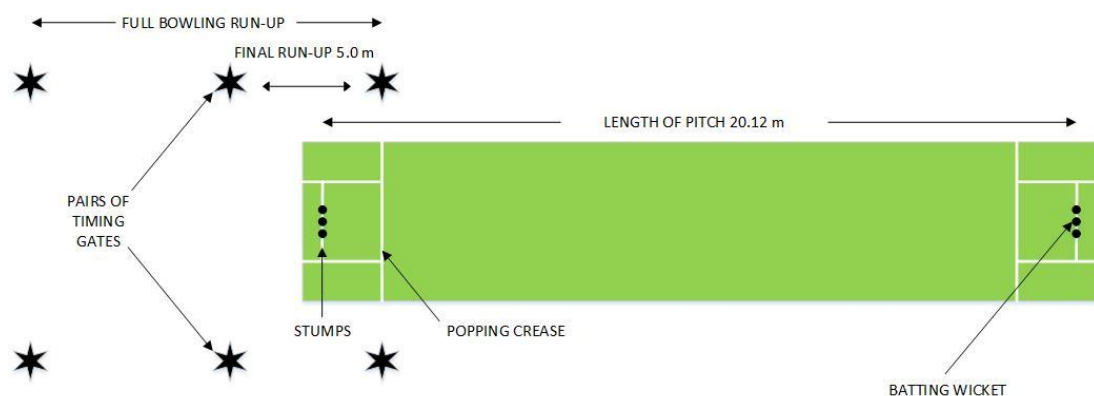


Figure 3.3. Cricket Australia-Australian Institute of Sport (CA-AIS) fast bowling skills test set up. Adapted from Duffield et al. (2009), and M. Portus et al. (2010).

Blood Collection

In experiment three (see Chapter 7.), venous blood samples were collected to determine creatine kinase (CK), uric acid (UA) and urea (see Blood Analysis). Venous blood samples were drawn by standard venepuncture technique from an antecubital vein, after 10-min in a supine position. Blood samples were collected via a 21-gauge needle (Vacurette®, Greiner Bio-One Ltd, Stonehouse, UK), into a 6 ml lithium heparin vacuette tube (Vacurette®, Greiner Bio-One Ltd, Stonehouse, UK). All blood sampling was undertaken in a semi-recumbent position to restrict changes in plasma volume (Rowell, 1993). Once collected, all samples were stored on ice for 30-min before being centrifuged (Thermo Scientific Hereaus, Labofuge 400 R, Fisher Scientific UK, Loughborough, UK) at 2300 rpm for 10-min at 4 °C, and separated plasma was pipetted and stored in Eppendorf tubes (Sarstedt, Numbrecht, Germany) at -80 °C until biochemical analysis. The blood collection time points are highlighted in Chapter 7 (see Table 7.1.).

Blood Analysis

Plasma creatine kinase (CK; U·L⁻¹), uric acid (UA; μmol·L⁻¹) and urea (mmol·L⁻¹) were measured *ex vivo* using the ABX Pentra 400 auto-analyser system (Horiba, Montpellier, France). According to manufacturer's instructions, CK was quantified using an assay kit (ABX Pentra, CK NAC CP) in accordance with the coupled enzymatic reactions described by Oliver (1955) and Rosalki (1967). UA was quantified using an assay kit (ABX Pentra, Uric Acid CP) based on the Trinder

enzymatic reaction as described by Fossati, Prencipe, and Berti (1980). Urea was quantified using an assay kit (ABX Pentra, Urea CP) as described by Talke and Schubert (1965). Each specific parameter was subjected to the necessary calibration and quality control methods (ABX Pentra Multical, ABX Pentra CK Control, ABX Pentra N Control and ABX Pentra P Control) as instructed by the manufacturer.

Saliva Collection

In experiment three (see Chapter 7), saliva samples were collected using a 10 mm x 38 mm salivary oral swab (Salivette, Sarstedt, Numbrecht, Germany) to determine salivary cortisol concentrations ([sCort] see Cortisol). Players were instructed to gently chew the swab for one minute and then place the swab in the storage cryovial. Players refrained from eating and were asked to drink only water for 60-min before collection. All saliva samples were stored on ice for 30-min before being centrifuged at 2300 rpm for 2-min at 4 °C. Saliva was pipetted off and stored in Eppendorf tubes (Sarstedt, Numbrecht, Germany) at -80 °C until biochemical analysis. The saliva collection time points are highlighted in Chapter 7 (see Table 7.1.).

Cortisol

Salivary cortisol (ng·mL⁻¹) was quantified using a commercially available Enzyme-Linked Immunosorbent Assay (ELISA, Abcam, ab154996, Abcam, Cambridge, UK). Briefly, 25 µL of standard and sample was added to their respective wells in duplicate. Two hundred µL of dilute Cortisol-HRP Conjugate was added and was incubated for one hour at 37 °C (Heraeus Laboratory Incubator, Fisher Scientific Ltd, Loughborough, UK). Following extensive washing (3 x wash stages using 300 µL of wash buffer solution per wash), 100 µL of TMB Substrate Solution was added to each

well and the plate was incubated for 15-min in the dark, at room temperature. One hundred μL of Stop Solution was added to all wells to terminate the colour reaction. Cortisol was quantified by measuring the absorbance of each well at 450 nm (using a Tecan Infinite M200 Pro plate reader, Tecan, Männedorf, Switzerland), followed by comparison with the known standards provided in the kit.

Session Rating of Perceived Exertion

Rating of perceived exertion (RPE) was obtained within 30-min after each trial using a modified RPE scale (Foster et al., 2001) (see Appendix C). Match load was calculated by multiplying the RPE score with playing minutes (sRPE).

Statistical analysis

Statistical analysis was performed using the Statistical Package for the Social Sciences (SPSS) for Windows (IBM SPSS Statistics, version 23, IBM Corp., Armonk, NY, USA.). Data are reported as means and standard deviations (mean \pm *SD*), calculated by conventional procedures combined with magnitude-based inferences (Batterham & Hopkins, 2006; Cohen, 2013; R. D. Johnston et al., 2013).

Prior to any specific statistical procedures employed, the dependant variables undertook a principle decision analysis, identifying whether they followed a recognised pattern or distribution (Fallowfield, Hale, & Wilkinson, 2005). Providing the data followed a known distribution (normal), then, subsequent parametric statistical tests were performed. In contrast, non-parametric statistical tests were performed, if the data failed to follow a normal distribution. Normal distribution describes a symmetrical, bell-shaped curve, with the greatest frequency of scores in the middle, with smaller frequencies towards the extremes (Gravetter & Wallnau,

1999; Pallant, 2001). The normal distribution model is especially applicable in situations where the measurements of people are involved (Fallowfield et al., 2005).

A further important consideration when analysing data is how the measurement error relates to the magnitude of the measurement variable (Atkinson & Nevill, 1998). Generally, when the amount of random error increases as the measured values increase, data are said to be heteroscedastic and can show deviations from the typical normal bell-shaped distribution curve (Atkinson & Nevill, 1998; Zar, 1999). Consequently, heteroscedastic data typically found in measures of athletic performance should be measured on a ratio scale and, therefore, should be transformed logarithmically before analysis (Atkinson & Nevill, 1998; McLaren et al., 2016). Log-transformation therefore addresses the problem of heteroscedasticity, providing an estimate of the typical percentage error (Hopkins, 2000; Hopkins, Marshall, Batterham, & Hanin, 2009). You obtain the estimate of the typical percentage error of the original variable by multiplying the typical error of the log-transformed measure by 100 (Hopkins, 2000).

Where conventional statistical analysis was used (“*P*-value” or “*r*-value”), it was supplemented with confidence intervals (CI). Confidence intervals are used to represent the precision of the estimate of the test statistic or relationship in the population data set (Hopkins, 2000; van Schaik & Weston, 2016). Common approaches when using CI’s are to cite either 95% or 90% CI’s. Hopkins et al. (2009) suggest that a 90% CI should be adopted as the default level of confidence, because it implies quite reasonably that an outcome is clear, if the true value is very unlikely to be substantial, either in a positive or negative sense. Furthermore, the authors (Hopkins et al., 2009) state, that using 90% rather than 95% also serves to discourage the reader from reinterpreting the outcome as significant or non-significant at the 5% level

(Sterne & Smith, 2001). Secondly, Hopkins (2000) further rationalises that a 95% CI is far too stringent for a decision limit, especially when participants are athletes. In light of these suggestions, only Chapter 4 will use a 95% CI, due to the nature of the data, whereas the remaining experimental chapters (Chapters 5 – 7) will present the findings with a 90% CI.

The final application of magnitude-based inferences within this thesis is that of determining the smallest worthwhile change (SWC; %). Within sport and exercise science literature, the SWC is typically determined in one of three ways (van Schaik & Weston, 2016). Firstly, practitioners or researchers may have accrued years of practical experience within a sport and, therefore, can develop an understanding of what change in performance is needed to justify their chosen training intervention (van Schaik & Weston, 2016). Secondly, the quantification and publication of the within-athlete variability between performance in multiple sports provides practitioners or researchers with important data pertaining to the smallest effect needed to detect a worthwhile change in performance (van Schaik & Weston, 2016). Lastly and importantly for this thesis, in the absence of a previous statistical quantification of what would constitute the SWC in performance, inferences can be based on a standardised small threshold change (0.2 *SD*) (Batterham & Hopkins, 2006; van Schaik & Weston, 2016).

4. A Descriptive Analysis of Fast Bowling Workload and Playing Schedule in a Domestic Professional Cricket Season

4.1. Introduction

Traditionally, the playing schedule of a professional cricketer involved predominantly multiday (MD) cricket, resulting in considerable breaks between matches and series (Orchard et al., 2015). However, further professionalization of both international and domestic cricket has led to traditional playing schedules evolving and expanding. This has resulted in players competing for much of the year, experiencing periods of condensed fixtures with shorter winter breaks, which is regarded as a threat to team performance and player health (Carling et al., 2016; Ekstrand et al., 2004; Orchard et al., 2015). Now, professional cricketers regularly compete in three different match formats, consisting of MD and limited overs (One-day and Twenty20 [T20]) cricket, respectively (Hulin et al., 2014; McNamara et al., 2015a; McNamara et al., 2013; Petersen, Pyne, Portus, et al., 2011). As a result of this expansion, professional cricketers, specifically fast bowlers, are now potentially exposed to regularly playing in a high volume of matches and are likely to switch between match formats (MD vs. limited overs), undergoing large, irregular variations in match bowling loads in short time frames (J. A. Johnstone et al., 2014; Noakes & Durandt, 2000; Orchard et al., 2010; Orchard et al., 2009).

These scheduling changes, coupled with added travel (national or international), provide possible challenges for coaches and support staff due to the insufficient time for recovery, whilst increasing the propensity of injury, especially amongst fast bowlers (Dennis et al., 2004; Dennis et al., 2003; Dennis et al., 2005; Orchard et al.,

2015). Collectively, this highlights the importance of effective, accurate monitoring of external fast bowling loads (number of overs and balls bowled). Moreover, it is logical that bowler classification (opening and support bowlers) is also likely to influence fast bowling loads, as there is an inherent reliance on opening bowlers, as they are typically perceived as being the most capable of taking wickets (Petersen, Pyne, Portus, & Dawson, 2008) and thus more likely to be required to bowl. Although the rules are very different, the basic concept of cricket is similar to baseball (Dennis et al., 2003). Research by Love, Aytar, Bush, and Uhl (2010) compared pitch volume between starting pitchers (S-O) and combined starter/reliever pitchers (CS) and found significant differences ($P \leq 0.05$) between innings pitched (S-O; 6.0 ± 1.0 vs CS; 4.0 ± 1.3) and number of pitches per appearance (S-O; 97.0 ± 10.0 vs CS; 68.0 ± 19.0), respectively. Therefore, by applying a similar classification to fast bowlers, it should allow for the identification of bowling workload exposure data and the associated variability relative to competition format, which, in turn, may assist in necessary player and workload management practices (Carling et al., 2015; McNamara et al., 2015a; Olivier et al., 2016).

Several longitudinal investigations have reported on fast bowling workloads and the associated injury rates in both junior and senior professional cricketers (Dennis et al., 2004; Dennis et al., 2003; Dennis et al., 2005; Hulin et al., 2014; Orchard et al., 2009). Research by Hulin et al. (2014) investigated whether acute and chronic bowling workloads were associated with increased injury risk. Match data were collected during a 6-year period from 28 fast bowlers, equating to a total of 43 individual seasons. Bowling workloads were estimated by summing the total number of deliveries bowled per week (acute workload) together with 4-week rolling average

(chronic workload) to provide external workload data. The results showed a highly significant interaction ($p = \leq 0.01$) between acute bowling workloads in the current week and injury, with higher bowling loads linked with a lower injury risk. The data were further analysed to provide a training-stress balance score (expressed as a percentage), where the acute bowling load is divided by the chronic load. The results identified that a negative training-stress balance in relation to external bowling workload was significantly associated with an increased risk of injury (relative risk [RR] = 2.1; 95% CI 1.81 to 2.44; $p = 0.01$) in the following week. Sixty-three percent of all injuries occurred one week after a negative training-stress balance. Furthermore, it was shown that bowlers with an acute bowling workload of more than 200% compared with chronic load had a RR of 3.3 (95% CI 1.50 to 7.25; $p = 0.033$) and 2.9 (95% CI 1.14 to 7.40; $p = 0.044$) in comparison with bowlers with a training-stress balance between 50-99% and less than 49%, respectively.

Similarly, Orchard et al. (2009) investigated whether acutely high bowling loads were associated with increased injury risk following competition. Data were collected over 10-consecutive seasons from 129 fast bowlers, totalling 2715 individual seasons. Subsequent analysis was completed to provide comparisons between high and low bowling workloads and the likelihood of injury within the subsequent weeks. The first key finding was in those bowlers who bowled more than 50-overs in a match (high workload). They experienced an increased RR of 1.77 (95% CI 0.95 to 3.32) and 1.77 (95% CI 1.05 to 2.98), than those who bowled less than 50 overs in the subsequent 14- and 21-day periods, respectively. Moreover, bowlers who bowled more than 30 overs in the second innings of a match were 2.42 (95% CI 1.38 to 4.26) times more likely to develop an injury than those with lower bowling volumes in the subsequent 28-days.

Earlier studies provided a more comprehensive analysis of fast bowling workloads and the associated injury risk by collecting both training and competition workload data. The earlier of the two studies took data from two consecutive seasons from 90 fast bowlers yielding 9044 observations (Dennis et al., 2003), with the latter presenting data pertaining to 12 fast bowlers from a single season yielding 1001 observations (Dennis et al., 2004). These studies explored the possibility of differing fast bowling thresholds. Bowlers with weekly loads higher than the team mean of 188 deliveries (RR = 1.4; 95% CI 0.9 to 1.6) (Dennis et al., 2003) or 203 deliveries (RR = 6.0; 95% CI 1.00 to 35.91) (Dennis et al., 2004) were both shown to be at an increased risk of injury. Likewise, those with an average lower than the weekly team mean (123 deliveries) were also shown to be at an increased injury risk (RR = 1.4; 95% CI 1.0 to 2.0) (Dennis et al., 2003). Furthermore, it was shown that too many consecutive bowling sessions (≥ 5) in a 7-day period were associated with an increased injury risk (RR = 4.5; 95% CI 1.02 to 20.12) (Dennis et al., 2004). Moreover, Dennis and colleagues (Dennis et al., 2003) also highlighted that, in those instances where bowlers demonstrated ≤ 2 - (RR = 2.4; 95% CI 1.6 to 3.5) or > 5 -days (RR = 1.8; 95% CI 1.1 to 2.9) between bowling sessions, bowlers were at an increased risk of injury than those bowlers with an average of 3-3.99 days between bowling sessions. Collectively, these studies clearly demonstrate that fast bowlers are associated with the highest injury rates. However, this appears to be multifactorial. Initially, there appears to be a delay in the increased risk of injury following high bowling loads. With the inclusion of both training and competition bowling load data, research has made upper and lower fast bowling thresholds apparent. Moreover, it may be suggested that, to reduce injury risk, fast bowlers should not have extended periods without bowling.

To date, research detailing the increased professionalism of cricket and the resultant increase in playing schedules is limited to one study of international cricketers (Noakes & Durandt, 2000). The results from this study show that, across a 30-year period (1970 to 1998-99), the number of available days for cricket increased by 280%. The increased professionalization of cricket, the expansion of limited overs cricket, specifically T20 and the aforementioned research all now contribute to presenting further challenges for player management (Petersen, Pyne, Portus, et al., 2011). Several studies from professional soccer have identified the effects of fixture congestion on physical performance and injury rates (Bengtsson, Ekstrand, & Hagglund, 2013; Carling et al., 2015; Carling, Le Gall, & Dupont, 2012; Carling et al., 2016; Carling, Orhant, & LeGall, 2010; Dellal, Lago-Penas, Rey, Chamari, & Orhant, 2015; Dupont et al., 2010). Although fixture congestion is regarded as a threat to team performance in other team sports such as soccer, the extent to which cricketers and fast bowlers are exposed to these increased periods of fixture congestion still remain unclear.

Despite there being substantial literature associated with fast bowling workloads and injury rates in cricket and fixture congestion and injury in other team sports, no information exists detailing differences among fast bowling workloads, especially since the increased professionalism of cricket. Therefore, the aims of this study were (a) to provide a detailed descriptive analysis of external fast bowling workloads for both opening and support bowlers, and (b) to describe chronic and acute differences in external fast bowling loads relative to bowler classification. We hypothesize that

bowler classification (opening or support bowlers) will result in different bowling workloads and number of appearances.

4.2. Methods

Experimental Approach to the Problem

This prospective observational study investigated a typical playing schedule experienced by professional cricketers throughout a 28-week regular domestic county season (April – September), with separate but not independent analysis of fast bowling workloads. Fast bowling workloads were determined from fixture scorebooks and calculated by evaluating the total frequency of bowling deliveries. Further analysis was performed to identify the total frequency of competition (MD [County Championship], OD [Pro40] or T20) deliveries. The dependant variables of bowling load were frequency of overs and deliveries bowled, both chronically (per month) and acutely (per week).

Subjects

Eight professional male medium to fast bowlers (mean \pm *SD*; age 27.3 ± 4.4 years) from the same County Cricket Club participated in this study. Bowling speed ($n = 2$ medium; $n = 3$ medium-fast; $n = 3$ fast-medium) and style ($n = 6$ right-arm; $n = 2$ left-arm) classifications were obtained from the open-access public website espncricinfo.com. Data were collected from all first-class fixtures spanning the 28-week regular season. The sample included information on the three separate forms of competition; County Championship ($n = 16$), Pro40 ($n = 12$) and T20 ($n = 16$) cricket, respectively. Data were obtained from the fixture scorebook, yet, all data can also be obtained from the open-access public website espncricinfo.com. The Department of

Sport, Health and Exercise Science Ethics Committee approved all experimental procedures and all data were anonymised before analysis.

Procedures

Data were recorded from all first-class fixtures spanning the 28-week regular season. Out of the 44 matches scheduled, 23 were played at home, with 21 matches away from home. Across all competitions, there were 15 matches won, 19 lost, 7 tied and 3 abandoned, with no result due to rain. Match exposure data were collected from the fixture scorebook and defined as play between teams from different clubs.

Individual Fast Bowling Workloads

Fast bowling data were collected from the fixture scorebook for each match, set up in a standardised manner, so that the bowler's role could be identified. Opening bowlers for each match were always listed first, with support bowlers listed underneath. This allowed for bowlers to be classified into two distinct categories: opening bowlers (O-B; $n = 2$) and support bowlers (S-B; $n = 6$). Opening bowlers were bowlers who always functioned as commencing the bowling, whereas support bowlers were bowlers who commenced bowling once the opening bowlers had ceased bowling.

Match Exposure

To determine match exposure, data were characterised into weekly blocks running from Monday to Sunday. One-week data, together with monthly means, were calculated for overs and deliveries bowled, respectively. The 1-week data are represented as an acute workload, whereas the monthly means are represented as the chronic bowling workloads.

Statistical Analysis

Using SPSS (IBM SPSS Statistics, v.23, IBM Corp., Armonk, NY, USA.), all data were confirmed as being normally distributed and are reported as means and standard deviations (mean \pm *SD*). An independent samples *t*-test was used to determine the statistical differences between-groups for 1) competition type 2) appearances and 3) months, respectively. A one-way analysis of variance (ANOVA) was used to determine the statistical significance across each month of competition for bowling volume (overs and deliveries). If significant main effects were found, a Tukey post hoc test analysis was performed to locate the differences. The level for statistical significance was set at $P \leq 0.05$. Data are reported as the mean difference and 95% confidence interval (95% CI). Cohen's *d* effect size (ES) statistic was used to determine the practical significance observations (Cohen, 2013). Effect sizes were classified as: 0.00-0.19, 0.20-0.59, 0.60-1.19, 1.20-1.99 and ≥ 2.00 were considered trivial, small, moderate, large and very large, respectively (Hopkins et al., 2009).

4.3. Results

In the 2011 domestic season, the eight fast bowlers were recorded as having participated in a total of 192 matches equating to 227 bowling innings. Descriptive data pertaining to the total number of matches, innings, appearances and total number of overs and deliveries bowled for each format of competition, by bowler classification are presented in Tables 4.1. and 4.2., respectively.

Table 4.1. Extrinsic fast bowling competition load variables for bowlers participating in the 2011 Season.

Bowler Number	Total number of matches	Total number of innings	Innings bowled per appearance	Total number of competition bowling days	Total number of non-fixtured days	Competition bowling days:non-fixtured days
1 (O-B)	19	30	1.58	61	100	1.64
2 (O-B)	34	43	1.26	76	85	1.12
3 (S-B)	31	39	1.26	70	91	1.30
4 (S-B)	36	46	1.28	78	83	1.10
5 (S-B)	23	23	1.00	29	132	4.55
6 (S-B)	12	17	1.42	33	128	3.89
7 (S-B)	30	20	0.67	63	98	1.56
8 (S-B)	7	9	1.29	19	142	7.47

O-B = Opening bowler; S-B = Support bowler

Individual Fast Bowling Workloads

Throughout the whole season, there were large differences in the total number of overs bowled between O-Bs and S-Bs, with O-Bs bowling a significantly greater volume (296.1 overs; 95% CI 37.8 to 554.4; ES = 1.80 [large]; $P = 0.03$). Likewise, during the same period, O-Bs were shown to bowl a significantly greater total number of deliveries than S-Bs (1764.8 balls; 95% CI 183.0 to 3346.7; ES = 2.84 [very large]; $P = 0.03$), respectively. Moreover, during MD cricket, there were very large differences, found in both the total number of overs (289.9 overs; 95% CI 88.2 to 491.6; ES = 4.33 [very large]; $P = 0.01$) and deliveries bowled (1739.3 balls; 95% CI 529.3 to 2949.3; ES = 4.33 [very large]; $P = 0.01$). Again, O-Bs displayed the highest bowling volumes. Further analysis explored the differences of fast bowling workloads between the first and second innings of MD cricket, yielding similar findings. There was a very large, significant difference in the total number of overs (159.7 overs; 95% CI 22.6 to 296.8; ES = 2.91 [very large]; $P = 0.03$) and deliveries (954.8 balls; 95% CI 126.2 to 1783.4; ES = 2.88 [very large]; $P = 0.03$) bowled in the first innings of multiday cricket. Likewise, across the second innings, there was a very large, significant difference in the total number of overs (130.2 overs; 95% CI 61.6 to 198.7; ES = 5.24 [very large]; $P = 0.004$) and deliveries (779.5 balls; 95% CI 364.1 to 1194.9; ES = 5.19 [very large]; $P = 0.004$) bowled. The bowling volumes for both innings were significantly greater among O-Bs vs S-Bs, respectively. Further analysis explored the differences between total number of overs and deliveries bowled per session of MD cricket. The results from this analysis show similar outcomes, namely that O-Bs bowled significantly more overs (2.8 overs; 95% CI 2.4 to 3.3; ES = 0.98 [moderate]; $P < 0.01$) and deliveries (17.4 balls; 95% CI 14.6 to 20.2; ES = 0.98 [moderate]; $P < 0.01$) bowled per session than S-Bs, respectively.

Table 4.2. Descriptive statistics for the extrinsic fast bowling competition load variables for each individual competition format (mean \pm *SD*).

	Opening bowler (O-B)	Support bowler (S-B)	<i>P</i> Value
Total number of overs bowled	511.8 \pm 66.0	215.7 \pm 138.5	<i>P</i> = 0.03
Total number of deliveries bowled	3071.0 \pm 396.0	1306.2 \pm 849.0	<i>P</i> = 0.03
Total number of MD overs (County Championship)	452.1 \pm 23.9	162.2 \pm 110.1	<i>P</i> = 0.01
Total number of MD deliveries (County Championship)	2712.5 \pm 143.5	973.2 \pm 660.3	<i>P</i> = 0.01
Total number of overs bowled per session of MD cricket	4.6 \pm 3.3	1.8 \pm 2.7	<i>P</i> < 0.01
Total number of deliveries bowled per session of MD cricket	28.1 \pm 19.8	10.7 \pm 16.1	<i>P</i> < 0.01
Total number of OD overs (Pro40)	42.6 \pm 17.8	30.2 \pm 24.7	<i>P</i> = 0.55
Total number of OD deliveries (Pro40)	255.5 \pm 106.8	181.2 \pm 148.4	<i>P</i> = 0.55
Total number of T20 overs	17.2 \pm 24.3	17.6 \pm 15.3	<i>P</i> = 0.98
Total number of T20 deliveries	103.0 \pm 145.7	105.5 \pm 91.6	<i>P</i> = 0.98

MD = multiday; OD = one-day; T20 = Twenty20 cricket

There were small, non-significant differences in the total number of overs (12.4 overs; 95% CI -35.0 to 59.8; ES = 0.58 [small]; $P = 0.55$) and deliveries (74.3 balls; 95% CI -210.0 to 358.7; ES = 0.58 [small]; $P = 0.55$) bowled in OD cricket between O-Bs and S-Bs. There was a trivial, non-significant difference in the total number of overs bowled in T20 cricket between O-Bs and S-Bs (-0.4 overs; 95% CI -34.6 to 33.8; ES = -0.05 [trivial]; $P = 0.98$). A trivial, non-significant difference in the total number of deliveries bowled in T20 cricket between O-Bs and S-Bs was found (74.3 balls; 95% CI -207.6 to 202.6; ES = -0.02 [trivial]; $P = 0.98$).

Match Exposure

Descriptive statistics of the total number of appearances for each format of competition by bowler classification are presented in Table 4.3. There was a very large, significant difference in the total number of appearances in MD cricket between O-Bs and S-Bs (5.5 appearances; 95% CI 0.3 to 10.7; ES = 2.23 [very large]; $P = 0.04$). A small, non-significant difference was found in the total number of appearances (0.7 appearances; 95% CI -6.7 to 8.0; ES = 0.21 [small]; $P = 0.83$) in OD cricket between O-Bs and S-Bs. A trivial, non-significant difference was found in the total number of appearances (-2.8 appearances; 95% CI -15.1 to 9.4; ES = -0.41 [trivial]; $P = 0.59$) in T20 cricket between O-Bs and S-Bs, respectively.

Table 4.3. Descriptive statistics for frequency of match exposure for each individual competition format (mean \pm *SD*).

	Opening bowler (O-B)	Support bowler (S-B)	<i>P</i> Value
Total number of days engaged in competition	68.5 \pm 10.6	48.7 \pm 24.6	<i>P</i> = 0.18
MD competition (County Championship)	14.0 \pm 0.0	8.5 \pm 4.9	<i>P</i> = 0.04
OD competition (Pro40)	7.0 \pm 2.8	6.3 \pm 3.8	<i>P</i> = 0.83
T20 competition	5.5 \pm 7.8	8.3 \pm 5.8	<i>P</i> = 0.59

MD = multiday; OD= one-day; T20 = Twenty20

Collectively, no significant differences were found in the chronic number of overs (*P* = 0.11) or deliveries (*P* = 0.10) bowled across each of the six successive months of the competitive season. However, further analysis revealed that there was a significant interaction between bowler classification and fast bowling workloads dependant on the month of the competition (Figure 4.1. & Figure 4.2.). Specifically, significant differences were found in the opening month (April) and, subsequently, within the penultimate month (August) of the season.

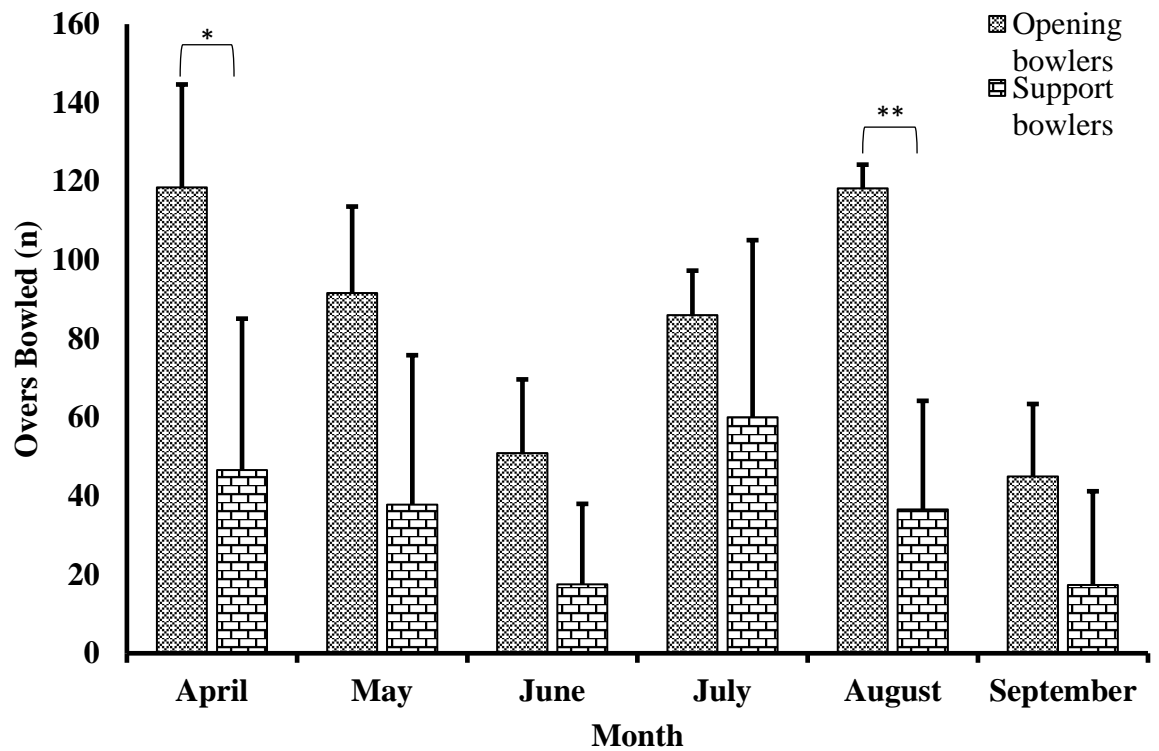


Figure 4.1. Comparison of overs bowled across the entire season between bowler classifications. *Denotes a significant difference in overs bowled compared to support bowlers ($P \leq 0.05$). **Denotes a significant difference in overs bowled compared to support bowlers ($P \leq 0.01$). Data presented as mean \pm *SD*.

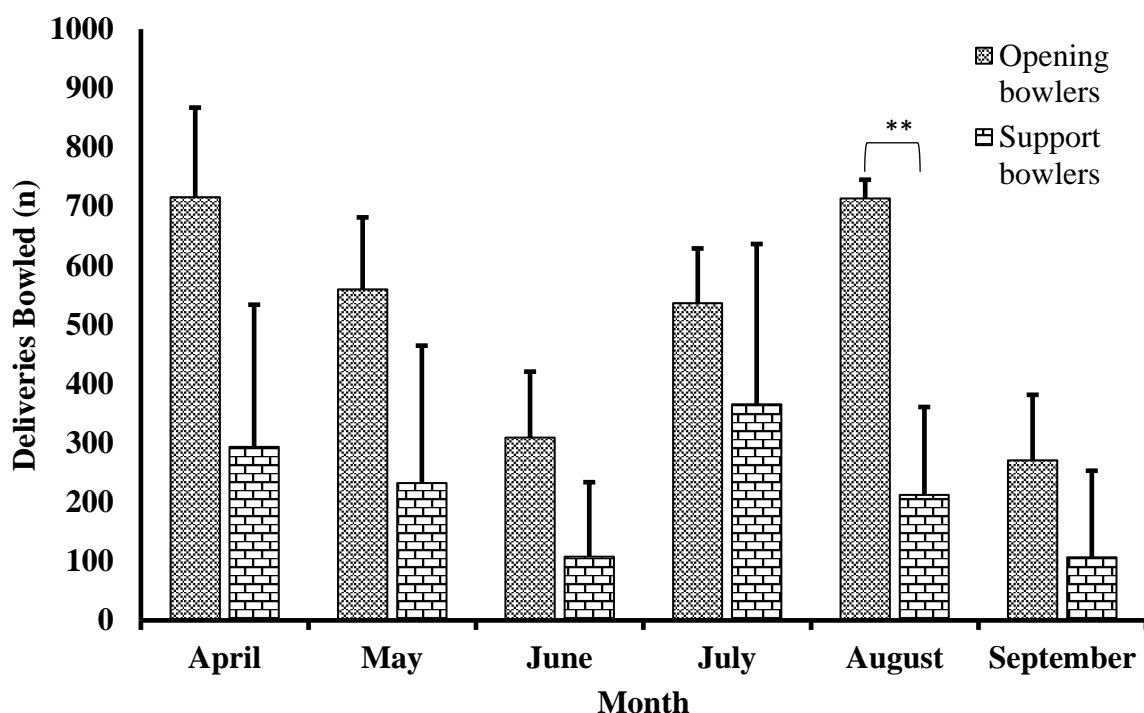


Figure 4.2. Comparison of deliveries bowled across the entire season between bowler classifications. **A significant difference in number of deliveries bowled compared to support bowlers ($P \leq 0.01$). Data presented as mean \pm *SD*.

There was a very large, significant difference in the total number of overs bowled in April between O-Bs and S-Bs (71.9 overs; 95% CI -1.5 to 145.2; ES = 2.23 [very large]; $P = 0.05$). Similarly, a very large, yet non-significant difference was found in the total number of deliveries bowled in April (422.8 balls; 95% CI -33.1 to 878.8; ES = 2.16 [very large]; $P = 0.06$). Large, non-significant differences were found in both the total number of overs (53.7 overs; 95% CI -17.8 to 125.3; ES = 1.79 [large]; $P = 0.12$) and deliveries (327.5 balls; 95% CI -107.4 to 762.4; ES = 1.85 [large]; $P = 0.12$) bowled in May between O-Bs and S-Bs, respectively. There were large, non-significant differences in the total number of overs (33.4 overs; 95% CI -6.9 to 73.7; ES = 1.70 [large]; $P = 0.09$) and deliveries (201.3 balls; 95% CI -45.8 to 448.5; ES = 1.69 [large]; $P = 0.09$) bowled in June between O-Bs and S-Bs. There was a moderate,

non-significant difference in both the total number of overs (26.0 overs; 95% CI -23.1 to 75.0; ES = 0.92 [moderate]; $P = 0.24$) and deliveries (171.3 balls; 95% CI -329.4 to 672; ES = 0.94 [moderate]; $P = 0.43$) bowled in July between O-Bs and S-Bs, respectively. Very large, significant differences were found in both the total number of overs (81.6 overs; 95% CI 31.1 to 132.2; ES = 4.85 [very large]; $P = 0.008$) and deliveries (501.0 balls; 95% CI 229.1 to 772.9; ES = 5.56 [very large]; $P = 0.004$) bowled in August between O-Bs and S-Bs, respectively. Large, non-significant differences in both the total number of overs (27.6 overs; 95% CI -18.4 to 73.6; ES = 1.31 [large]; $P = 0.19$) and deliveries (164.0 balls; 95% CI -188.3 to 446.3; ES = 1.26 [large]; $P = 0.20$) bowled in September between O-Bs and S-Bs were found.

Table 4.4. Monthly descriptive statistics of overs and deliveries bowled for each month of competition across the three different competition formats (mean \pm SD).

	Opening bowler (O-B)	Support bowler (S-B)	P Value
April total number of overs	118.5 \pm 26.2	46.6 \pm 38.5	$P = 0.05$
April total number of deliveries	716.0 \pm 151.3	293.2 \pm 240.7	$P = 0.06$
May total number of overs	91.6 \pm 22.0	37.8 \pm 38.0	$P = 0.12$
May total number of deliveries	560.0 \pm 121.6	232.5 \pm 232.2	$P = 0.12$
June total number of overs	50.9 \pm 18.7	17.5 \pm 20.5	$P = 0.09$

June total number of deliveries	309.0 ± 111.7	107.7 ± 126.0	<i>P</i> = 0.09
July total number of overs	86.0 ± 11.3	60.0 ± 45.8	<i>P</i> = 0.47
July total number of deliveries	536.5 ± 92.6	365.2 ± 271.4	<i>P</i> = 0.43
August total number of overs	118.3 ± 6.0	36.6 ± 27.6	<i>P</i> < 0.01 (0.008)
August total number of deliveries	713.5 ± 31.8	212.5 ± 148.4	<i>P</i> < 0.01 (0.004)
September total number of overs	45.0 ± 18.4	17.4 ± 23.8	<i>P</i> = 0.19
September total number of deliveries	270.5 ± 111.0	106.5 ± 146.6	<i>P</i> = 0.21

There was a significant difference found in both the cumulative number of overs and deliveries bowled across the 28-week competitive season ($P < 0.001$). Specifically, these differences between fast bowling workloads and bowler classification were found within the opening eight weeks of competition and, subsequently, within the final two weeks of competition (Figure 4.3.).

There was a very large, significant difference in the total number of overs (75.4 overs; 95% CI 16.3 to 134.5; ES = 3.48 [very large]; $P = 0.02$) and deliveries (449.7 balls; 95% CI 74.5 to 824.8; ES = 3.38 [very large]; $P = 0.02$) bowled in week 3 between O-B and S-B, respectively. Similarly, there was a very large, significant difference in the total number of overs bowled between O-B and S-B in week 6 (110.9 overs; 95% CI

3.7 to 218.1; ES = 2.29 [very large]; $P = 0.04$). During week 27, there was a very large, significant difference in the total number of overs (294.6 overs; 95% CI 13.8 to 575.3; ES = 2.90 [very large]; $P = 0.04$) and deliveries (1780.7 balls; 95% CI 110.6 to 3450.7; ES = 2.99 [very large]; $P = 0.04$) bowled between O-B and S-B, respectively. Within the final week of the season, there was a very large, significant difference in the total number of overs (300.3 overs; 95% CI 17.4 to 583.1; ES = 2.72 [very large]; $P = 0.04$) and deliveries (1813.5 balls; 95% CI 132.1 to 3494.9; ES = 2.79 [very large]; $P = 0.03$) bowled between O-B and S-B.

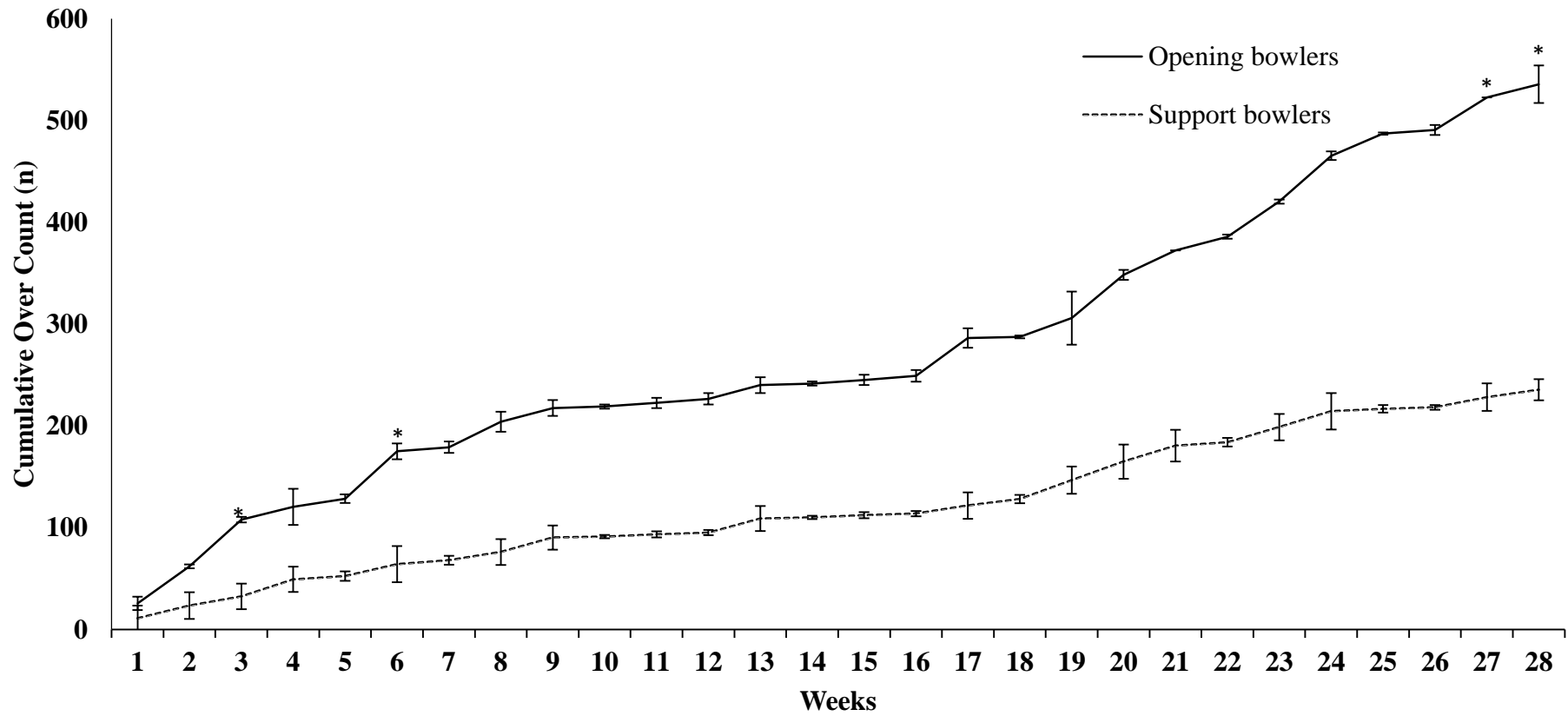


Figure 4.3. Comparison of cumulative overs bowled for the 28-week regular season between bowler classifications. *A significant difference in number of overs bowled between O-B and S-B ($P \leq 0.05$). Data presented as mean \pm *SD*.

4.4. Discussion

Presented in the current experimental chapter are the typical competition fast bowling workloads (deliveries) of domestic fast bowlers over the course of an entire season, differentiating between both bowler classification and competition format. Although numerous studies have described fast bowling workloads and the occurrence of injury over multiple seasons (Dennis et al., 2004; Dennis et al., 2003; Hulin et al., 2014; Orchard et al., 2015), there is still a lack of descriptive data identifying the typical competition fast bowling loads, especially since the increased popularity of limited overs cricket. The main finding of this study supports our initial hypothesis, that there were significant differences in both the total number of overs and deliveries bowled between opening and support bowlers, respectively. Moreover, significant differences were found between bowler classification, competition format and cumulative bowling loads when analysed on a chronic and acute basis.

Firstly, our fast bowling descriptive data shows that (with the exception of one support bowler # 7), fast bowlers typically bowl within each innings of appearance, resulting in an innings per appearance ratio of > 1 . Therefore, irrespective of bowler classification, we have shown that fast bowlers frequently bowl in multiple innings during competition. This is perhaps a result of the nature of MD cricket, whereby bowlers are typically required to bowl in both innings of competition. Furthermore, we identified the ratio between competitive bowling days and non-fixtured days. Our results show that O-Bs experienced a competition/non-fixtured playing ratio of 1.38, whereas S-Bs experienced a playing ratio of 3.3 days. Therefore, irrespective of bowler classification, all bowlers are typically involved in a greater number of non-competition days than competition days.

Dennis et al. (2003) also investigated the importance of this ratio and provided data identifying its relationship to injury. The results from this study identified that a dual workload threshold is present in fast bowling, highlighting that, compared with those bowlers with a mean of 3-3.99 days between bowling sessions, bowlers with a mean of < 2 days (RR = 2.4) or ≥ 5 days (RR = 1.8) between bowling sessions resulted in significantly increased injury risk. Similarly, Hulin et al. (2014) also explored the protective effects of bowling workload thresholds. However, the authors compared weekly (acute) fast bowling volumes against a four-week average (chronic). The results from this study showed that, when simultaneous large bowling volumes are applied over an acute and chronic period, the subsequent injury risk is decreased. Therefore, by systematically increasing the chronic bowling workload, it is likely that these larger volumes can offer a positive physical adaptation, minimising fatigue and ultimately preventing injury (Banister et al., 1975; Hulin et al., 2014). Although we have no injury data to support our findings, our data highlights that O-Bs may be at an increased injury risk. However, the competition/non-fixtured playing ratio among S-Bs falls within the threshold as suggested by Dennis et al. (Dennis et al., 2003). Therefore, it could be suggested that sufficient rest periods are present for S-Bs. However, O-Bs may be exposed to a potential increased risk of injury.

This study shows large to very large significant differences in the total number of overs and deliveries bowled between opening and support bowlers, respectively. Although the playing standard is comparable to our data, Dennis et al. (2004) identified that bowlers who sustained an injury during the season had a higher mean number of deliveries (235 balls) than those who did not sustain an injury (165 balls). Despite the number of deliveries reported in our study differing substantially from those described earlier (Dennis et al., 2004), it is probable that these differences are

associated with the recent developments in cricket and the increased scheduling of limited overs cricket. Consequently, in an attempt to identify the influence of this increased scheduling, we sought to explore fast bowling workloads relative to competition format. Collectively, we found very large significant differences in fast bowling loads within MD cricket, which was further identified among the first and second innings, respectively. Further exploration of MD cricket variables showed that, per session, bowlers would bowl a mean of 28 deliveries. Although we do not have any injury data, this finding has potential importance, in light of earlier research (Dennis et al., 2003), which identified that bowlers who bowled < 40 deliveries per session had an increased risk of injury compared with those who bowled > 40 deliveries (risk ratio 1.2). Interestingly however, our data shows trivial to small non-significant differences in fast bowling workloads between both forms of limited overs (Pro40 and T20) cricket. These findings would suggest that, within limited overs cricket, there isn't an increased reliance on opening bowlers, yet, the opposite is apparent during MD cricket.

Throughout the six-month domestic season (April – September), we found differences between bowler classification and competition bowling workloads on a monthly and weekly basis, respectively. Our results show very large significant differences between the number of overs bowled in April and the number of overs and deliveries bowled in August between opening and support bowlers, respectively. Similarly, Dennis et al. (2004) also present data on the monthly and weekly deliveries bowled, yet they relate their findings to injury risk. The results from this study show that those who bowl a mean of > 522 deliveries per month (no RR data) and those who bowl > 203 deliveries per week (RR = 6.0) were at a significant risk of injury ($P < 0.01$). Therefore, it is plausible to suggest that, although no injury data were present,

during the majority of the season, opening bowlers may have been at an increased injury risk than support bowlers. Additionally, the observed patterns in monthly bowling workloads may coincide with the frequency of MD cricket, whereby a greater number of overs and subsequent deliveries are likely to be bowled. Therefore, further research is warranted, using multiple clubs to identify whether these findings are limited to a single team or apparent as a result of the playing schedule.

In addition to the monthly and weekly breakdown of fast bowling loads, we also present cumulative over and delivery count data for the 28-week domestic season. These results show very large, significant differences in the number of cumulative overs bowled in weeks 3, 6, 27 and 28, between O-Bs and S-Bs, respectively. With the exception of week 6, the same differences are found in the number of deliveries bowled. These findings identify periods within the season, typically in the first and last quarters, where there is a significant reliance on opening bowlers.

Collectively, our findings both reinforce the importance of monitoring fast bowling workloads and highlight the potential challenges for coaches and practitioners. Specifically, the latter must ensure that both opening and support bowlers attain sufficient workloads or rest periods, which will promote the positive adaptations required to tolerate the physical demands of cricket and ultimately reduce injury risk (Hulin et al., 2014; Petersen et al., 2010). This has further importance, given that playing schedules regularly include periods of limited over cricket, which have been shown to elicit the lowest workloads. Moreover, this data can be used in training prescription for both return to play following injury and during specific periods of the season where there are increased bowling and scheduling demands. Although, in all probability, this data has already been recognised by coaching staff, these findings may indicate that a more individualised approach to workload monitoring and training

prescription differentiating between bowler classifications is required. Although we extend the work of others (Dennis et al., 2004; Dennis et al., 2003; Hulin et al., 2014; Orchard et al., 2015), we acknowledge that the increased scheduling of both international and domestic cricket calendars now represent one of the greatest challenges in terms of injury prevention.

Moreover, despite the large emphasis placed on fast bowling workloads in this chapter and associated injury from existing literature, unfortunately, data pertaining to cricket locomotion for determining physiological measures was absent. This is of increased interest, as it can objectively quantify the level of physical exertion and stress each player endures relative to each specific playing role in both training and competition (Cummins et al., 2013; Cunniffe et al., 2009; Waldron et al., 2011). Furthermore, such information may aid in training prescription and recovery strategies, which may facilitate performance gains (Boyd et al., 2011) and reduce injury risk (Hulin et al., 2014). One solution to achieve this can be the use of GPS systems with an integrated accelerometer, typically referred to as micro-electro-mechanical system (MEMS). These systems allow for the real-time collection of human locomotive data to examine sporting movement patterns in a convenient, efficient and detailed manner (Cummins et al., 2013; Dellaserra, Gao, & Ransdell, 2014).

In summary, this chapter described the typical competition bowling workloads of fast bowlers, differentiating between bowler classification and competition format, respectively. Our results demonstrated that in comparison with S-Bs, O-Bs bowled a significantly greater cumulative volume of overs, spanning the entire season. Extrapolating these findings, we were able to identify that this was a direct result of

competing in MD cricket. Moreover, we were able to show that during periods of limited overs cricket (OD and T20), there were no differences in competition bowling workloads. Given the lack of differences in bowling workloads during these scheduling periods and the ever-increasing popularity of limited overs cricket, further research is required to investigate and improve the understanding of the physical response of fast bowling in limited overs cricket, specifically as descriptive bowling load characteristics fail to account for variations and may lead to an assumption that all balls bowled are equal. The introduction of MEMS technology within cricket is ever-emerging and now allows for routine monitoring of the physical demands of training and competition. Moreover, utilising this technology provides an opportunity to enhance the monitoring of fast bowling for both injury prevention and specifically for this thesis, performance outcomes.

5. Using Microtechnology to Evaluate the Between- and Within-Match

Variability of Professional Twenty20 Cricket Fast Bowlers

This experimental chapter has formed the basis of the publication detailed below:

Bray, J.W., Fogarty, M., Barrett, S., Lovell, R., and Abt, G. (2016). Using microtechnology to evaluate the between- and within-match variability of professional Twenty20 cricket fast bowlers. *Professional Strength and Conditioning – UKSCA*, 43(December), 19-26.

5.1. Introduction

Cricket is a popular team sport, comprising two teams of 11 players, typically played within Commonwealth countries (McNamara et al., 2015a; McNamara et al., 2013). Players are classified into specific roles within the team, yet all are required to field throughout the course of the opposition's batting innings (McNamara et al., 2013). Unlike many other team sports, players will compete in three different match formats consisting of limited overs (Twenty20 [T20] and 50-over) and multiday ([MD] 4 or 5 day) cricket (Hulin et al., 2014; McNamara et al., 2015a; McNamara et al., 2013; Petersen, Pyne, Portus, et al., 2011). Consequently, external fast bowling loads (overs and balls bowled) will vary depending on match format. Fast bowlers usually account for 3 to 5 of the 11 players on each team (McNamara et al., 2015a) and have been shown to have the highest physical training loads of this population (McNamara et al., 2015a; Petersen et al., 2010). Moreover, the prevalence of injuries within this population has risen in recent years, which has been attributed to the inclusion of more T20 cricket (Hulin et al., 2014; Orchard et al., 2015; Orchard et al., 2010; Orchard et al., 2009).

Given the differences in match format, there is an increasing interest in quantifying the physical demands experienced by cricketers during training and competition (Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009; Vickery et al., 2014). Such interest has elicited the use of time-motion analysis (TMA) as an objective tool to measure the physical demands as validated in other team sports (Boyd et al., 2011). Recent developments in TMA now integrate wearable athlete tracking technology of global positioning systems (GPS) and tri-axial accelerometers, allowing for a more practical, time-efficient approach to traditional methods (R. J. Johnston et al., 2012). This integrated microtechnology is now typically referred to as a micro-electro-mechanical system (MEMS) and provides a further means of capturing movement patterns and quantifying the training load within sporting environments (Cummins et al., 2013; Gastin, McLean, et al., 2013; McNamara et al., 2015a; McNamara et al., 2013; Vickery et al., 2014). Measures of training load are further characterised into physiological and psycho-biological responses (internal training load) and player movement patterns and activity profiles (external training load) (Cummins et al., 2013). Monitoring enables sport scientists and/or those working with cricketers to objectively quantify the level of physical exertion and stress each player endures relative to their specific playing role in both training and competition (Cummins et al., 2013; Cunniffe et al., 2009; Waldron et al., 2011), thus informing training prescription and recovery strategies, which may facilitate performance gains (Boyd et al., 2011) and reduce injury risk (Hulin et al., 2014).

Within cricket, specifically fast bowling, TMA research incorporating MEMS technology has contributed to an increased understanding of the differences in match load and intensity across the different forms of competition and training (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen,

Pyne, Portus, Karppinen, et al., 2009). These studies have reported on the variability in movement patterns during One-day Internationals (Petersen, Pyne, Portus, Karppinen, et al., 2009) and T20 cricket (Petersen, Portus, et al., 2009). These findings highlight that international fast bowlers covered the greatest total distances of any position (Petersen, Pyne, Portus, Karppinen, et al., 2009). Aside from total distance (TD), a global measure of training load, fast bowlers also covered the greatest distances in high-speed locomotive activities across all formats of competition (Petersen et al., 2010). Specifically, Petersen et al. (2010) highlighted that, during T20 cricket, there were a 22% and 43% increase in hourly sprint distances for fast bowlers than during limited overs and multiday cricket, respectively (Stronach et al., 2014). Moreover, in a T20 innings, fast bowlers spent 9% of the total time sprinting (Petersen, Portus, et al., 2009; Petersen et al., 2010), which is comparable to findings in other team sports (Cunniffe et al., 2009; Gregson, Drust, Atkinson, & Salvo, 2010; Kempton et al., 2015; McLaren et al., 2016).

Recently, studies have also reported on tri-axial accelerometry (PlayerLoad™) within team sport environments (Barrett et al., 2015; Boyd et al., 2011, 2013; Gastin, McLean, et al., 2013; McNamara et al., 2013). PlayerLoad™ (PL) is a movement variable that uses the accelerometer embedded within the MEMS device to measure the frequency and magnitude of forward, sideways and upward accelerations to determine a player's external training load (Boyd et al., 2011; R. J. Johnston et al., 2012). Additionally, this measure allows for an increased understanding of the physical demands that are not based on running activities, such as the fast bowling action. Furthermore, these accelerometers measure at 100 Hz, making them more sensitive to subtle movements compared to GPS, which typically measures global displacement at only 1-10 Hz (Mooney et al., 2013). Research has reported on the

reliability of PL (Boyd et al., 2011) and how it can quantify external loads in competition and simulated team sport activity (Barrett et al., 2015; Boyd et al., 2013; R. J. Johnston et al., 2012). Knowledge about this technology for monitoring cricket match play (specifically fast bowling) is limited to one study on elite age-group cricketers (McNamara et al., 2013). In this study, McNamara and colleagues (2013) provide comparisons between key external training load variables between fast- and non-fast bowlers in training and competition, respectively. Specifically, fast bowlers accumulated a greater PL during both training (703 vs 598 arbitrary units [AU]) and competition (912 vs 679 AU), respectively. However, these findings may be somewhat expected, given that fast bowlers are required to participate in both batting and fielding drills and, therefore, the increased PL may be attributed to the strong relationship with TD (Aughey, 2011; Boyd et al., 2013) and running kinematics (Barrett et al., 2014), respectively.

The complex and intermittent characteristics typically experienced in team sport performance are unstable and subject to variation between matches (Gregson et al., 2010; Kempton et al., 2014; McLaren et al., 2016). During competition, the physical demands of fast bowling depend on both match type and the team strategy employed by the captain (McNamara et al., 2015a). While few studies have reported the movement demands of cricket match play (Cummins et al., 2013; Petersen, Portus, et al., 2009), the majority of published work has focused on quantifying physiological responses to simulated fast bowling (Duffield et al., 2009; Minett et al., 2012a, 2012b). Between-match variation in physical activity has been reported in professional soccer competition (Gregson et al., 2010) and, more recently, in both codes of professional rugby (Gastin, McLean, et al., 2013; Kempton et al., 2014; McLaren et al., 2016). However, data on the between-match variability specific to T20 fast bowling is limited

to Australian national cricketers (Petersen, Portus, et al., 2009; Petersen et al., 2010). Indeed, this research highlights the variability in player movement patterns, yet, more importantly, the results show that T20 cricket imposes greater high-speed locomotive demands compared to multiday and one-day cricket, respectively (Petersen et al., 2010; Stronach et al., 2014). Moreover, given the notable differences between match formats and the recent global development of domestic T20 competitions, the variability of physical performance and bowling demands are likely to differ from this published data. Consequently, quantification of both within- and between-match variability data will contribute to enhancing the methods and accuracy of monitoring fast bowling loads within competition.

Therefore, the aims of this investigation were (a) to profile fast bowling and investigate the between-match variability of key external training load variables with the use of MEMS devices during a competitive block of T20 cricket, which is now typically experienced by professional cricketers, and (b) to use the same technology and external training load variables to profile and investigate the within-match between-over variability.

5.2. Methods

Experimental Approach to the Problem

Eight professional fast bowlers from an English County Cricket Club were used to examine both between-match and within-match between-over variability of player movement characteristics in the NatWest T20 Blast competition. The movement characteristics were measured using a portable MEMS device consisting of GPS (5 Hz) and tri-axial accelerometer (100 Hz) technology. The movement parameters and locomotive classifications analysed were selected based on previous team sport

research (R. J. Johnston et al., 2012; McLaren et al., 2016; Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009).

Subjects

During the 2014 and 2015 domestic seasons, eight professional male fast bowlers (mean \pm *SD*; age 24.9 ± 6.5 years; body mass 86.5 ± 8.5 kg; height 187.9 ± 4.1 cm) from the same County Cricket Club volunteered to participate in this study. Bowling speed ($n = 3$ medium; $n = 1$ medium-fast; $n = 5$ fast-medium; $n = 1$ fast) and style ($n = 7$ right-arm; $n = 1$ left-arm) classifications were obtained from the open-access public website espncricinfo.com. Of the total number of participants, up to four fast bowlers wore a MEMS device during any given match. The Department of Sport, Health and Exercise Science Ethics Committee approved all experimental procedures and the study conformed to the declaration of Helsinki (World Medical, 2013). All players were free from injury or any other medical condition that would have prohibited participation. Before participating in the study, players were informed of all testing procedures and written informed consent was obtained. All bowlers had previously been familiarised with the MEMS device by wearing it during training sessions or non-competition matches.

Procedures

Data were measured during all NatWest T20 Blast fixtures. Fifty-three match files were collected from 18 matches during the 2014 ($n = 10$) and 2015 ($n = 8$) seasons, respectively. During these two consecutive seasons, 11 matches were played at home and 7 matches were played away from home, with 5 matches won, 11 lost and 1 tied. All matches were played on a professionally prepared first-class county cricket oval

within the United Kingdom, conforming to and meeting the requirements of the MCC Laws of Cricket (MCC, 2013).

Players wore an individual MEMS device (MinimaxX Team Sports v2.5, Catapult Innovations, Melbourne, Australia; mass 64.5 g; size 0.9 x 0.5 x 0.2 cm) encased within a neoprene vest, which housed the device between the scapulae. The MEMS device included a GPS device sampling at 5 Hz and a tri-axial piezoelectric linear accelerometer (Kionix, KXP94), sampling at 100 Hz. As recommended, each bowler wore the same MEMS device throughout all testing procedures (R. J. Johnston et al., 2015; Petersen, Pyne, Portus, & Dawson, 2009). Approximately 30-min before each match, the units were switched on to ensure that they were able to establish a satellite lock (≥ 4 satellites for ≥ 15 -min). The measurement error (technical error of measurement [TEM]) in the MEMS devices used for TD, low-speed (mean running speed ≤ 14.4 km·h⁻¹) and high-speed (mean running speed ≥ 14.4 km·h⁻¹) running distance during simulated team sport activities is reported to be 2.0%, 4.3% and 10.8%, respectively (R. J. Johnston et al., 2012; Petersen, Pyne, Portus, & Dawson, 2009). However, caution is required when interpreting shorter, higher speed locomotive activities, as these devices have been reported to underestimate sprint distance (R. J. Johnston et al., 2012; Petersen, Pyne, Portus, & Dawson, 2009). Moreover, the tri-axial accelerometer embedded within the MinimaxX devices has been reported to provide a highly reliable ($< 2\%$ CV) measure of PL in both laboratory (Boyd et al., 2011) and team sport simulations (Barrett et al., 2015; R. J. Johnston et al., 2012).

Throughout the testing period, the mean number of satellites that were found to be available for signal transmission using Catapult Sprint software (Sprint, Version

5.1.0, Catapult Innovations, Melbourne, Australia) were 9 ± 3 , which is similar to that previously reported (Jennings et al., 2010a; Waldron et al., 2011). The mean HDOP was 2.2 ± 2.0 . A HDOP of 1 indicates an optimal geometrical positioning of orbiting satellites for accurate monitoring of position (Jennings et al., 2010a; Waldron et al., 2011; Witte & Wilson, 2005). No data were omitted due to poor signal quality.

Movement demands were quantified using TD, which were further characterised into arbitrary speed zones and descriptors, in line with previous studies (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009) (see Chapter 3. Table 3.1.). The aim of our study was not to validate these speed zones, but to use them in order to compare our data to previous studies. Furthermore, we also reclassified the speed zones into a broader range allowing for further comparisons with existing literature (Kempton et al., 2014; Kempton et al., 2015; McLaren et al., 2016). The zones included; low-speed ($LSRD \leq 14.4 \text{ km}\cdot\text{h}^{-1}$) and high-speed ($HSRD \geq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance, respectively. High-speed locomotive efforts are reported with a dwell time of 0.2 s in an attempt to reduce errors that can occur in the smoothing of data used by the software (Petersen, Pyne, Portus, & Dawson, 2009). In addition to GPS parameters, PL expressed in arbitrary units (AU) was calculated in Sprint (Catapult Innovations, Melbourne, Australia), which is a modified vector magnitude expressed as the square root of the sum, as previously described (Boyd et al., 2011; Montgomery et al., 2010). Data were downloaded post-match using Sprint software (V5.1.0, Catapult Innovations, Melbourne, Australia) and subsequently analysed and processed by applying the proprietary intelligent motion filter. Each match file was subsequently split into specific reference periods, which were then used to construct performance profiles for the whole match and bowling only periods. All external training load variables were represented in absolute and

relative terms, indicative of volume and intensity, respectively. Relative measures were calculated as the absolute measure divided by the on-field playing time. The minimum number of matches per player was set at three (McLaren et al., 2016), giving a total of 53 match observations.

Between-Match Variation

To calculate the between-match variation for all fast bowlers, the following external training load variables were used: TD, low-speed running distance (mean running speed $\leq 14.4 \text{ km}\cdot\text{h}^{-1}$), high-speed running distance (mean running speed $\geq 14.4 \text{ km}\cdot\text{h}^{-1}$), total sprint distance (mean running speed $\geq 18 \text{ km}\cdot\text{h}^{-1}$), total number of sprints completed (n), peak speed ($\text{km}\cdot\text{h}^{-1}$) and PL (AU).

Within-Match Between-Over Variation

Within-match between-over variation was calculated for all fast bowlers using the same external training load variables (as detailed above). However, this analysis only included the bowling only periods. To construct these periods, each individual match file was split into each individual over. An individual over was cropped, so that data obtained included the initial run-up of the first delivery and all subsequent movements and actions until cessation of the final delivery (see Section 3. *Cropping of data*). The minimum number of completed overs bowled per match was set at two (up to 4-overs bowled). This resulted in a total of 172 specific over observations totalling 1070 deliveries (including extras).

Statistical Analyses

Raw match training load data are presented as the mean \pm *SD*. Prior to statistical analysis, all data were log-transformed to reduce the error occurring from non-uniform residuals, typically experienced in athletic performance (McLaren et al., 2016). Subsequently, data were analysed using a mixed effects linear model (SPSS v.23, Armonk, NY: IBM Corp) to estimate the between-match and within-match between-over variability. Variability was expressed using the coefficient of variation (CV%; typical error expressed as a percentage of the mean) (Hopkins, 2000). CVs were also presented with 90% confidence intervals (90% CI) as markers of the uncertainty of the estimates (McLaren et al., 2016). The smallest worthwhile change (SWC%) in external training load measures was calculated as 0.2 x between-player *SD* (Hopkins et al., 2009; Kempton et al., 2014; McLaren et al., 2016). The minimum criterion change required to produce a probable significant change for between-match and within-match between-over fast bowler match loads was calculated via the magnitude-based inference approach, using a custom-made spreadsheet (Batterham & Hopkins, 2006; Hopkins, 2004; Kempton et al., 2014).

5.3. Results

The environmental conditions of all completed matches were 22.9 ± 4.6 °C and $56.9 \pm 19.1\%$ relative humidity (RH), respectively. The mean match duration was 79.6 ± 5.8 min (7.3 %CV) with 19.7 ± 0.6 overs bowled (3.0 %CV). Individually, the mean bowling duration was 12.1 ± 3.5 min (31.0 %CV) with a spell length of 3.3 ± 1.2 overs (35.6 %CV). Absolute and relative descriptive data summarising movement categories contributing to TD covered are reported in Table 5.1. This data is further categorised to include the bowling only period.

Table 5.1. Descriptive fast bowlers ($n = 8$) external training load data (mean \pm SD).

	Whole match	Bowling only period
MEMS parameters (ABS)		
TD (m)	4878 \pm 1190	1206 \pm 438
LSRD (m)	4199 \pm 1017	845 \pm 309
HSRD (m)	692 \pm 250	364 \pm 154
TSD (m)	384 \pm 164	251 \pm 131
Total Sprint Number (n)	30 \pm 13	18 \pm 7
Peak Speed ($\text{km}\cdot\text{h}^{-1}$)	29 \pm 4	28 \pm 4
PL (AU)	359 \pm 91	95 \pm 33
MEMS parameters (REL)		
TD ($\text{m}\cdot\text{min}^{-1}$)	65.7 \pm 11.5	104.9 \pm 15.7
LSRD ($\text{m}\cdot\text{min}^{-1}$)	56.5 \pm 9.5	73.9 \pm 10.6
HSRD ($\text{m}\cdot\text{min}^{-1}$)	9.3 \pm 3.1	31.9 \pm 7.9
TSD ($\text{m}\cdot\text{min}^{-1}$)	5.2 \pm 2.3	21.7 \pm 8.6
Sprint Number ($n\cdot\text{min}^{-1}$)	0.4 \pm 0.2	1.6 \pm 0.4
PL ($\text{AU}\cdot\text{min}^{-1}$)	4.8 \pm 0.9	8.3 \pm 0.9

TD = Total distance; LSRD = Low-speed running distance ($\leq 14.4 \text{ km}\cdot\text{h}^{-1}$); HSRD = High-speed running distance ($\geq 14.4 \text{ km}\cdot\text{h}^{-1}$); TSD = Total sprint distance ($\geq 18 \text{ km}\cdot\text{h}^{-1}$); PL = PlayerLoadTM; ABS = Absolute; REL = Relative

Between-Match Variability

The whole match and the bowling only period CV's ($\pm 90\%$ CI) are reported in Table 5.2., along with reference values for the SWC. The whole match data shows a clear increase in the mean variability from LSRD to HSRD (9.6 to 32.9), with the 90%

confidence intervals not overlapping. While there is also an increase in the mean variability from HSRD to TSD (32.9 to 49.0), there is an overlap in the confidence intervals. Similarly, within the bowling only period, there is a notable increase in the mean variability from LSRD to HSRD (47.9 to 60.4) and from HSRD to TSD (60.4 to 83.2), respectively. However, there is an overlap in all of the confidence intervals. Moreover, the same observations are apparent within the relative, between-match variability data.

Table 5.2. Between-match variation of external training load measures.

	Whole match		Bowling only period	
	CV (%; 90% CI)	SWC (%)	CV (%; 90% CI)	SWC (%)
MEMS parameters (ABS)				
TD (m)	10.6 (8.5 to 14.7)	3.1	48.2 (37.5 to 70.6)	14.9
LSRD (m)	9.6 (7.7 to 13.2)	2.8	47.9 (37.2 to 70.0)	14.8
HSRD (m)	32.9 (25.9 to 47.2)	9.9	60.4 (46.5 to 89.9)	19.0
TSD (m)	49.0 (38.1 to 71.9)	15.2	83.2 (63.1 to 127.4)	27.1
Total Sprint Number (<i>n</i>)	48.0 (37.3 to 70.2)	14.8	84.4 (64.0 to 129.5)	27.5
Peak Speed (km·h ⁻¹)	12.1 (9.7 to 16.8)	3.5	15.0 (12.0 to 20.9)	4.4
PL (AU)	12.3 (9.8 to 17.0)	3.6	52.6 (40.8 to 77.5)	16.4
MEMS parameters (REL)				
TD (m·min ⁻¹)	11.2 (8.9 to 15.4)	3.2	21.9 (17.4 to 30.9)	6.5

LSRD ($\text{m}\cdot\text{min}^{-1}$)	10.0 (8.0 to 13.7)	2.9	18.7 (14.9 to 26.2)	5.5
HSRD ($\text{m}\cdot\text{min}^{-1}$)	33.6 (26.4 to 48.2)	10.1	33.2 (26.1 to 47.6)	10.0
TSD ($\text{m}\cdot\text{min}^{-1}$)	49.6 (38.5 to 72.7)	15.3	54.3 (42.0 to 80.2)	16.9
Sprint Number ($n\cdot\text{min}^{-1}$)	48.5 (37.7 to 71.0)	15.0	36.8 (28.9 to 53.1)	11.2
PL ($\text{AU}\cdot\text{min}^{-1}$)	13.3 (10.6 to 18.4)	3.9	8.5 (6.8 to 11.7)	2.4

TD = Total distance; LSRD = Low-speed running distance ($\leq 14.4 \text{ km}\cdot\text{h}^{-1}$); HSRD = High-speed running distance ($\geq 14.4 \text{ km}\cdot\text{h}^{-1}$); TSD = Total sprint distance ($\geq 18 \text{ km}\cdot\text{h}^{-1}$); PL = PlayerLoad™; ABS = Absolute; REL = Relative. CV%: coefficient of variation and 90% confidence interval; SWC%: smallest worthwhile change (0.2 x between subject standard deviation)

Within-Match Between-Over Variability

The within-match between-over CVs ($\pm 90\%$ CI) along with SWC values are reported in Table 5.3. There is a clear increase in the mean variability from LSRD to HSRD (8.2 to 12.8) and from HSRD to TSD (12.8 to 17.1), with an overlap in confidence intervals. Likewise, within the relative variability data, there is also a clear increase in the mean variability from LSRD to HSRD (6.4 to 13.9). However, the confidence intervals do not overlap. Moreover, there is a clear increase in the mean variability from HSRD to TSD (13.9 to 18.6). However, the confidence intervals overlap. Global measures of match activity; TD and PL were subject to the least variability throughout.

Table 5.3. Within-match between-over variation (overs 2, 3 & 4, respectively) of external training load measures.

	Overall	
	CV (%; 90% CI)	SWC (%)
MEMS parameters (ABS)		
TD (m)	7.0 (5.5 to 10.2)	2.0
LSRD (m)	8.2 (6.5 to 12.0)	2.4
HSRD (m)	12.8 (10.0 to 18.9)	3.7
TSD (m)	17.1 (13.3 to 25.4)	5.0
Total Sprint Number (<i>n</i>)	12.3 (9.6 to 18.1)	3.6
Peak Speed (km·h ⁻¹)	5.9 (4.6 to 8.5)	1.7
PL (AU)	6.6 (5.2 to 9.6)	1.9
MEMS parameters (REL)		
TD (m·min ⁻¹)	5.9 (4.6 to 8.6)	1.7
LSRD (m·min ⁻¹)	6.4 (5.0 to 9.3)	1.8
HSRD (m·min ⁻¹)	13.9 (10.8 to 20.5)	4.0
TSD (m·min ⁻¹)	18.6 (14.4 to 27.7)	5.5
Sprint Number (<i>n</i> ·min ⁻¹)	12.0 (9.3 to 17.6)	3.5
PL (AU·min ⁻¹)	5.5 (4.3 to 8.0)	1.6

TD = Total distance; LSRD = Low-speed running distance (≤ 14.4 km·h⁻¹); HSRD = High-speed running distance (≥ 14.4 km·h⁻¹); TSD = Total sprint distance (≥ 18 km·h⁻¹); PL = PlayerLoad™; ABS = Absolute; REL = Relative. CV%: coefficient of variation and 90% confidence interval; SWC%: smallest worthwhile change (0.2 x between subject standard deviation)

5.4. Discussion

Presented in the current experimental chapter is the between-match and within-match between-over variability of domestic T20 competition fast bowling using MEMS technology. The main finding of this study is in agreement with existing literature, which states that high-speed locomotive activity (HSRD, TSD and number of sprints performed) is highly variable between-matches (Gregson et al., 2010; Kempton et al., 2014; Kempton et al., 2015; McLaren et al., 2016) and within-match between-overs. In addition, when the between-match reference period was reduced in time (bowling only period), variability typically increased. These findings highlight the difficulties when interpreting high-speed locomotive match data. Comparatively and again in agreement with existing literature, TD and PL both appeared to offer a more stable measure of external training load, both between-match (Kempton et al., 2014; Kempton et al., 2015; McLaren et al., 2016) and within-match between-over, respectively. These findings indicate that changes in more global measures in match loads may be interpreted with more accuracy than high-speed locomotive measures.

The descriptive match play data presented provide conflicting findings to the existing cricket literature that quantified movement patterns in professional cricket (Petersen, Portus, et al., 2009; Petersen et al., 2010). While our data show a similar proportion of total time spent sprinting (8% vs 8.5%, respectively) compared with those reported (Petersen, Portus, et al., 2009), we also highlight large differences in TD covered (5.0 km vs 8.5 km, respectively). These findings are somewhat surprising due to the similarities in sample size and playing standard. However, the number of match observations in this study were far greater than those previously reported (Petersen, Portus, et al., 2009).

The between-match CVs for high-speed locomotive activities reported in this study are similar to those previously reported in both professional cricket (Petersen et al., 2010) and other team sports, where it has been reported that high-speed running parameters elicit the highest degree of variability between-matches (Gastin, McLean, et al., 2013; Gregson et al., 2010; Kempton et al., 2014; McLaren et al., 2016). In contrast, TD was the parameter that displayed the least variability, which agrees with the existing literature (Petersen et al., 2010). However, the authors (Petersen et al., 2010) only provide a CV range (9-17%) and failed to distinguish between playing position and game format. Furthermore, when the between-match data is split from the whole match to the bowling only period, the variability in external training load measures typically increases substantially, with the exception of PL·min⁻¹. The increased variability in external training load measures as the length of reference period decreased was an expected outcome. This is a result of the length of observation period, which, in turn, reflects the amount of time points included in the analysis, which are likely to stabilise when more data points are included (Kempton et al., 2014).

A novel aspect of this study was the focus on within-match between-over variability. As before, our data indicates that high-speed locomotive activity was the most variable parameter. However, lower variability was observed in the more global measures of external training load, TD and PL. Moreover, this observed low degree of variability in PL could provide an additional consideration when quantifying external training load, further supporting earlier research (R. J. Johnston et al., 2012). Considerable reductions in the degree of variability across all parameters occur when comparisons are made with between-match data. Exploration of the data in this way has the potential to exclude constraints imposed by fielding position, which may be

responsible for the differences in between-match variability (Kempton et al., 2015). Such findings might be of particular practical relevance for sport scientists and practitioners when attempting to quantify the competitive demands of fast bowling. Therefore, by acknowledging this information, it may lead to an increased specificity when designing and planning appropriate training sessions, that aim to replicate physical performance and match demands (Kempton et al., 2014; McLaren et al., 2016). Moreover, by understanding true changes in both between- and within-match data, sport scientists and practitioners have the ability to effectively evaluate the demands of training within competition to highlight the effectiveness of certain performance interventions (Kempton et al., 2014; McLaren et al., 2016).

By using the CV and SWC, a progressive magnitude-based statistical approach has been suggested, with minimum thresholds providing a high probability ($> 75\%$ confidence) of significant changes in physical performance (Batterham & Hopkins, 2006; Hopkins et al., 2009; Kempton et al., 2014). It is often the role of sport scientists and practitioners to compare match performances within-players, to evaluate the demands of training with those of competition. Increasing the understanding of between- and within-match changes is fundamental in the planning process (Kempton et al., 2015; McLaren et al., 2016). Using this approach between-match, applying this for TD (CV 10.6%; SWC 3.1%), a minimum change of 13.8% is required to be confident that the change is real. When examining both HSRD (CV 32.9%; SWC 9.9%) and PL (CV 12.3%; SWC 3.6%), the minimum threshold for a probable change increases for HSRD (43.0%) and PL (16.1%), respectively. Similarly, when this statistical approach is applied to the within-match between-over data, minimum changes for TD (6.9%), HSRD (16.4%) and PL (8.4%) are identified.

The large between-match variability, specifically for HSRD and TSD, has important practical implications for interpreting physical match play data (Kempton et al., 2014; McLaren et al., 2016). Our data supports previous findings from both cricket and other team sports (Gastin, McLean, et al., 2013; Gregson et al., 2010; Kempton et al., 2014; McLaren et al., 2016; Petersen et al., 2010), that high-speed locomotive activities are inconsistent between- and within-matches, respectively (Kempton et al., 2014; Rampinini, Coutts, Castagna, Sassi, & Impellizzeri, 2007). While a single match observation will provide a snap shot of that match, multiple observations from many matches are needed to accurately describe the physical demands (Kempton et al., 2014; Rampinini et al., 2007). Ultimately, this data provides further evidence to suggest that several repeated measures are required to identify a true change in time motion analysis parameters. Specifically, practitioners should establish CVs specific to the athlete population in consideration. In contrast to high-speed locomotive activities, TD, LSRD, peak speed and PL were more stable both between-match and within-match between-over. Our data suggest that the loads obtained from these variables may appear to allow for a more informed interpretation of competition demands, compared to high-speed locomotive activities. However, when interpreting these findings, it is important to remember that fast bowlers within the same team can experience substantially different physical demands, dependant on the team strategy employed (McNamara et al., 2015a), the length of bowler run-up, duration of spell and/or number of deliveries bowled. Unfortunately, in this study, these factors were not accounted for and future studies should attempt to quantify the effects of these factors.

In summary, this chapter examined the between-match and within-match between-over variability of common MEMS training load measures in professional T20 match play. The results identified that global measures of performance TD and PL were relatively stable, with higher locomotive activities eliciting a higher degree of variability. Furthermore, when segmenting the match data into specific epochs (within-match between-over) this variability was markedly reduced. Our earlier findings (see Chapter 4) have failed to show differences between bowler classification and fast bowling workloads in OD cricket. Therefore, it would appear logical to apply a similar rationale to the additional limited overs cricket format (50-overs). Thus, further research is required, to explore in greater depth the between-match variability of MEMS training load data in OD cricket. Moreover, given the increased competition demands of OD vs. T20 cricket, a further consideration for sport scientists and practitioners is the quantification of fatigue as a direct result of increasing match demands and, consequently, bowling workloads. Therefore, further research is also required to identify the relationship of fatigue to the increases in physical match demands.

6. Neuromuscular Fatigue Responses During a Professional Cricket Season

6.1. Introduction

Cricket is a popular team sport, typically played within Commonwealth countries (McNamara et al., 2015a; McNamara et al., 2013). Recent increased interest in cricket has led to further professionalization of International and First-class county players, who can now regularly play a high volume of matches ($n = 100$ days approximately) per calendar year (J. Johnstone et al., 2013; Noakes & Durandt, 2000). Players are classified into specific roles, which include batsmen, fast bowlers, spin bowlers and wicket keepers, with fast bowlers typically accounting for 3 to 5 of the 11 players on each team (McNamara et al., 2015a). Unlike many other team sports, professional cricketers will compete in three different match formats consisting of limited overs (One-day [OD] and Twenty20 [T20]) and multiday ([MD] 4 or 5 day) cricket (Hulin et al., 2014; McNamara et al., 2015a; McNamara et al., 2013; Petersen, Pyne, Portus, et al., 2011). Consequently, fast bowling training loads (overs and balls bowled) will vary dependant on match format (Minett et al., 2012a). Specifically, a fast bowler in OD cricket may be required to complete a maximum of 60 repetitive high-intensity bowling episodes consisting of a run-up, followed by upper- and lower-body actions interspersed with periods of lower-intensity fielding activities (J. A. Johnstone et al., 2014; Minett et al., 2012b; Noakes & Durandt, 2000; Orchard et al., 2009). These repetitive high-intensity fast bowling episodes have been shown to evoke pronounced physiological responses in heart rate and blood lactate, respectively (Duffield et al., 2009).

Fatigue has been described as an acute impairment of performance that includes a reduction in the maximal voluntary force production by a muscle or muscle group and/or an increase in the perceived effort to exert a desired force or power (Gandevia, 2001; Rampinini et al., 2011). An accumulation of fatigue or incomplete recovery can influence performance substantially, especially during periods of regular competition (McLean et al., 2010). Therefore, objectively quantifying fatigue on a regular basis can provide meaningful information on the readiness of players to train and compete (Wehbe et al., 2015). In turn, this data has the potential to be beneficial to the overall season's performance (Gastin, Meyer, et al., 2013; McLean et al., 2010; Wehbe et al., 2015) and reduce injury risk (Hulin et al., 2014). One particular facet of fatigue, which has gained increasing interest amongst sport scientists and practitioners, is neuromuscular fatigue (NMF). Traditionally, NMF has been assessed using isolated forms of muscle action (Gandevia, 2001; Rampinini et al., 2011). However, recent evidence suggests that incorporating movements that involve the stretch-shortening cycle (SSC) is considered one of the more valid forms of examining neuromuscular fatigue, due to the similarities with movements involved in athletic performance (Gathercole et al., 2015b; C. P. McLellan et al., 2011b). It has been suggested that applied tests to monitor NMF in professional sport should be valid, objective, highly reliable and practical and should not compromise training (Fowles, 2006; Wehbe et al., 2015). Therefore, short maximal effort performance tests, specifically countermovement jump (CMJ) tests, have received significant examination in team sports.

Despite the popularity of CMJ tests to monitor NMF in other team sports (Andersson et al., 2008; Cormack et al., 2013; Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; R. D. Johnston et al., 2013; McLean

et al., 2010; C. P. McLellan et al., 2011b; Mooney et al., 2013; Thorlund, Aagaard, & Madsen, 2009), within cricket, specifically fast bowling, CMJ data is limited to spells of simulated fast bowling (Duffield et al., 2009; Minett et al., 2012a, 2012b). Although McNamara and colleagues (McNamara et al., 2013) did investigate fatigue and fast bowling training load variables of professional junior cricketers during a 10-day period of intensified competition (3 x 50-over; 2 x 2-day & 2 x T20 matches), unfortunately, they failed to present any CMJ data immediately following competition. Moreover, Duffield et al. (2009) identified physiological responses and bowling performance during simulated medium-fast bowling (2 x 6-over spells). There were no significant short-term (pre to post) differences found ($P = 0.6$, $d < 0.02$) in the (5 x) maximal vertical jump height for both spells, respectively.

Research by Minett and co-workers (Minett et al., 2012a) investigated the effects of mixed-method cooling on recovery of medium-fast bowling on consecutive days (day 1: 10-overs and day 2: 4-overs) in the heat using a variation of the same fast bowling simulation. Although no significant differences were found ($P = 0.25-0.88$; $d = 0.03-0.30$) in the (10 x) maximal CMJ height between conditions, a significant difference was found ($P < 0.05$) in CMJ height on day two. However, the authors failed to discuss this finding further. Similarly, same authors (Minett et al., 2012b) investigated the physiological effects of mixed-method pre-cooling on medium-fast bowling in the heat. The results from this study also found no significant differences ($P = 0.22-0.50$; $d = 0.18-0.45$) in the (10 x) maximal CMJ height between conditions pre to post. Collectively, the existing literature suggests that a spell or repeated spells of medium-fast bowling fail to induce significant fatigue. However, there is currently no evidence examining short-term fatigue following a limited overs cricket match. Therefore, quantifying the demands imposed on fast bowlers during match play is vital

to gain an understanding of the nature of and time-course of fatigue during both a single match and an entire season. This will allow sport scientists and practitioners to manage player fatigue and plan effective recovery.

Recent developments in TMA, with the integrated wearable athlete tracking technology such as GPS and tri-axial accelerometers now allow for routine analysis of the frequency and magnitude of movement in three dimensions (Boyd et al., 2011). An accelerometer measures at 100 Hz, making it more sensitive to subtle movements than GPS, which typically measures global displacement at only 1-10 Hz (Mooney et al., 2013). The cricket GPS research (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009) has contributed to an increased understanding of the differences in match load and intensity across the different forms of competition. Fast bowlers have been shown to cover the greatest total distances (TD) (Petersen, Pyne, Portus, Karppinen, et al., 2009) and the greatest distances in high-speed activity across all game formats (Petersen et al., 2010). As a result of the aforementioned physically demanding nature of fast bowling, it could therefore be expected that the stress associated with fast bowling may impair physical performance. However, unlike GPS, it is still unclear if accumulation of accelerometer derived matrix (PlayerLoad™; PL) can provide any indication of physical performance or is sensitive to NMF in fast bowling.

Despite previous research, limited data remains pertaining to the pattern of neuromuscular fatigue within limited overs cricket fast bowling. It is currently unclear whether such measures (match exercise intensity and NMF) are useful monitoring tools. Currently, no single marker has established sensitivity to detect overall fatigue in sporting populations (Coutts, Slattery, & Wallace, 2007). Therefore, the aim of this study was (a) to determine the neuromuscular fatigue response to limited overs fast

bowling across an entire season and (b) to determine whether fatigue effects the relationship between MEMS derived variables. We hypothesised that short-term fatigue would occur following limited overs cricket and this would be attenuated as a result of greater competition bowling workloads.

6.2. Methods

Experimental Approach to the Problem

The present study examined the SSC performance of fast bowlers to determine neuromuscular fatigue after limited overs cricket throughout a 22-week regular season (April – September), where matches were scheduled on a 7-day cycle. The dependant variables were NMF and match performance. To determine the NMF response to limited overs fast bowling, flight time during a CMJ was assessed on an electronic jump mat, pre- and post-competition. Match performances were measured using a MEMS device comprising GPS (5 Hz) and tri-axial accelerometer (100 Hz) technology. The movement parameters analysed were selected based on previous team sport research (McLaren et al., 2016; Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009). An understanding of short-term NMF following competition is important to determine recovery and effectively manage player preparation for subsequent matches.

Subjects

Six professional academy male fast bowlers (mean \pm *SD*; age 18.4 ± 1.0 years; body mass 80.8 ± 4.3 kg; height 183.1 ± 4.2 cm) from the same County Cricket Club participated in this study. Bowling speed ($n = 1$ medium; $n = 1$ medium-fast; $n = 4$ fast-medium) and style ($n = 6$ right-arm) classifications were obtained from the open-

access public website espnricinfo.com. Data were measured during all academy fixtures spanning the 22-week regular season. All players were free from injury or any other medical condition that would have prohibited participation. Before participating in the study, all players were familiarised with all testing procedures during training sessions or non-competition matches. Written informed consent was obtained from each player and all players were free to withdraw from the study at any time. Prior to all matches, players followed a prescribed pre-match routine (see Section 3. Subjects). The Department of Sport, Health and Exercise Science Ethics Committee approved all experimental procedures and the study conformed to the declaration of Helsinki (World Medical, 2013).

Procedures

Data were measured during all academy fixtures spanning the 22-week regular season. There were a total of 16 matches analysed. 9 matches were played at home and 7 matches were played away from home, with 10 matches won, 6 lost and 4 abandoned with no result due to rain. All matches were played at the same time of day (12:00 hours). The CMJ was assessed on an electronic jump mat between 11:00 – 11:30 hours pre-match following a standardised 10-min dynamic warm-up (CMJ-PRE). Depending on the outcome of the coin toss at start of play, the post-match CMJ test was conducted within 30-min after either bowling first (CMJ-FIRST) between 15:00 – 15:30 hours or bowling second (CMJ-SECOND) between 19:00 – 19:30 hours, respectively. Due to the applied nature of this research and the competition time constraints, the same pre-match standardised 10-min dynamic warm-up was not administered post bowling innings. However, each player still performed three

submaximal practice CMJs before the measurement trial. Match performance was assessed via MEMS technology.

The Countermovement Jump

Before performing the CMJ test, players completed a standardised 10-min dynamic warm-up session similar to that previously described, including dynamic stretches followed by a series of different running patterns progressively increasing in intensity (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010; McNamara et al., 2013). Players then performed three submaximal practice CMJs before the measurement trial. Each player then performed three CMJs, with 3-min of rest between each CMJ at a standard time between 11:00 – 11:30 hours pre-match. All CMJs were performed with hands held firmly on the hips and players were instructed to jump as high as possible. All jumps were performed at a self-selected countermovement depth (Cormack, Newton, McGuigan, & Cormie, 2008; McNamara et al., 2013). The best result from the three CMJs was used for analysis. The CMJ was performed on a commercially available electronic jump mat (Smart Jump, Fusion Sport, Queensland, Australia) operated by manufacturer software (Smart Speed, Fusion Sport, Queensland, Australia) to calculate flight time (FT [ms]). Coefficient of variation (CV) as a percentage of the FT was 3.7%.

Physical Performance

During competition, player movements were monitored via an individual MEMS device (MinimaxX Team Sports v2.5, Catapult Innovations, Melbourne, Australia; mass 64.5 g; size 0.9 x 0.5 x 0.2 cm) encased within a neoprene vest, which housed the device between the scapulae. The MEMS device included a GPS device sampling

at 5 Hz and a tri-axial piezoelectric linear accelerometer (Kionix, KXP94) sampling at a frequency of 100 Hz. As recommended, where possible, each bowler wore the same MEMS device throughout all testing procedures to avoid interunit error (Jennings et al., 2010b; R. J. Johnston et al., 2015). Approximately 30-min before each match, the units were switched on to ensure that they were able to establish a satellite lock (≥ 4 satellites for ≥ 15 -min). The MEMS device was switched off immediately after each match.

Throughout the testing period, the mean number of satellites that were found to be available for signal transmission using Catapult Sprint software (Sprint, Version 5.1.0, Catapult Innovations, Melbourne, Australia) were 7 ± 1 , which is similar to that previously suggested for the optimal use of GPS technology (Jennings et al., 2010a; Waldron et al., 2011). The mean HDOP was 1.8 ± 0.2 . A horizontal dilution of position of 1 indicates an optimal geometrical positioning of orbiting satellites for accurate monitoring of position (Jennings et al., 2010a; Waldron et al., 2011; Witte & Wilson, 2005). No data were omitted due to poor signal quality.

Movement demands were quantified using TD, which was further characterised into arbitrary speed zones, to facilitate comparisons with previous studies (Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009) (see Chapter 3. Table 3.1.). All high-speed running efforts (mean running speed $\geq 14.4 \text{ km}\cdot\text{h}^{-1}$) are reported with a dwell time of 0.2 s. The MEMS units used in this study have been shown to be a valid and reliable measure of movement patterns in cricket (Petersen, Pyne, Portus, & Dawson, 2009). In addition to GPS parameters, PL, expressed in arbitrary units (AU), was calculated in Sprint (Catapult Innovations, Melbourne, Australia), which is a modified vector magnitude expressed as the square root of the sum of that previously described (Boyd et al., 2011;

Montgomery et al., 2010). These MEMS devices have provided a highly reliable (%CV < 2) measure of PL in laboratory-based simulations (Boyd et al., 2011) and, more recently, during simulated team sport play (Barrett et al., 2015).

Data were downloaded post-match using Sprint (V5.1.0, Catapult Innovations, Melbourne, Australia) software and subsequently analysed and processed by applying the proprietary intelligent motion filter. Each match file was subsequently split into specific reference periods, which allowed bowling-only profiles to be established. To generate the bowling-only profiles, each individual over was cropped, so that data obtained included the initial run-up of the first delivery and all subsequent movements and actions until cessation of the final delivery (see Section 3. *Cropping of data*). All training load variables were represented in absolute (ABS) and relative terms (REL; i.e. $\text{m}\cdot\text{min}^{-1}$), indicative of volume and intensity, respectively. Relative measures were calculated as the absolute measure divided by the on-field playing time. The minimum number of matches per player was set at 3 (McLaren et al., 2016), giving a total of 57 match observations.

In addition to the MEMS analysis, the games were analysed using a simple hand notational procedure, typically obtained from the scorebook. The descriptive performance variables analysed were match duration (min and overs) and individual bowling duration (min, overs and balls). Individual overs bowled were further categorised into arbitrary bowling workload descriptors, based on the maximum number of overs permitted to bowl (12-overs) in competition; LOW (≤ 4 overs), MODERATE (5-8 overs) and HIGH (9-12 overs), respectively.

Session Rating of Perceived Exertion

Session rating of perceived exertion (RPE) was obtained within 30-min after each match using a modified RPE scale (Foster et al., 2001). Match load was calculated by multiplying the RPE score with playing minutes (sRPE).

Statistical Analyses

In order to determine changes in neuromuscular fatigue, traditional significance testing combined with magnitude based inferences was performed (Batterham & Hopkins, 2006; Cohen, 2013; R. D. Johnston et al., 2013). All data were confirmed as being normally distributed and therefore presented as the mean \pm *SD*. A repeated measures (time * load) analysis of variance (ANOVA) was used to determine the statistical significance of bowling volume on CMJ performance (FT). If significant main effects were found, a Bonferroni post hoc test analysis was performed to locate the differences. The level for statistical significance was set at $P \leq 0.05$. Data are reported as the mean difference and 90% confidence interval (90% CI). Cohen's *d* effect size (ES) statistic was used to determine the practical significance observations (Cohen, 2013). Effect sizes were classified as 0.00-0.19, 0.20-0.59, 0.60-1.19, 1.20-1.99 and ≥ 2.00 and were considered trivial, small, moderate, large and very large, respectively (Hopkins et al., 2009).

All MEMS device variables were log-transformed to reduce the error occurring from non-uniform residuals, typically experienced in athletic performance (McLaren et al., 2016). Subsequently, data were analysed using a mixed effects linear model to estimate the between-match variability. Variability was expressed using the coefficient of variation (CV%; typical error expressed as a percentage of the mean) (Hopkins, 2000). CVs were also presented with 90% CI as markers of the uncertainty of the estimates (McLaren et al., 2016). The smallest worthwhile change (SWC %) in

MEMS data was calculated as 0.2 x between-player SD, as outlined in previous research (Hopkins et al., 2009; Kempton et al., 2014; McLaren et al., 2016). The minimum criterion change required to produce a probable significant change for between-match fast bowling loads was calculated via the magnitude-based inference approach, using a custom-made spreadsheet (Batterham & Hopkins, 2006; Hopkins, 2004; Kempton et al., 2014).

Pearson's product-moment correlations (r) were calculated to assess relationships between Δ CMJ, MEMS parameters, RPE and descriptive performance variables. Further bowling workload-specific (LOW, MODERATE, HIGH) correlations were calculated, to assess the same relationships after controlling for bowling volume. The following criteria were adopted to identify the magnitude of the correlation < 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 – 0.99, nearly perfect (Hopkins et al., 2009). Correlations of ≤ 0.1 have not been reported. All statistical analysis was performed using SPSS (IBM SPSS Statistics, v.23, IBM Corp., Armonk, NY, USA.).

6.3. Results

Neuromuscular Fatigue

There was a very large, significant reduction in flight time pre to post bowling innings (Δ 19 ms; 90% CI 7 to 31; ES = 5.4 [very large]; $P = 0.008$). Similarly, a very large, significant reduction in flight time between CMJ-PRE to CMJ-FIRST was observed (Δ 19 ms; 90% CI 2 to 35; ES = 4.7 [very large]; $P = 0.05$). However, a non-significant, very large reduction in flight time was observed in CMJ-PRE to CMJ-SECOND (Δ 20 ms; 90% CI -1 to 41; ES = 4.9 [very large]; $P > 0.05$) (Figure 6.1.).

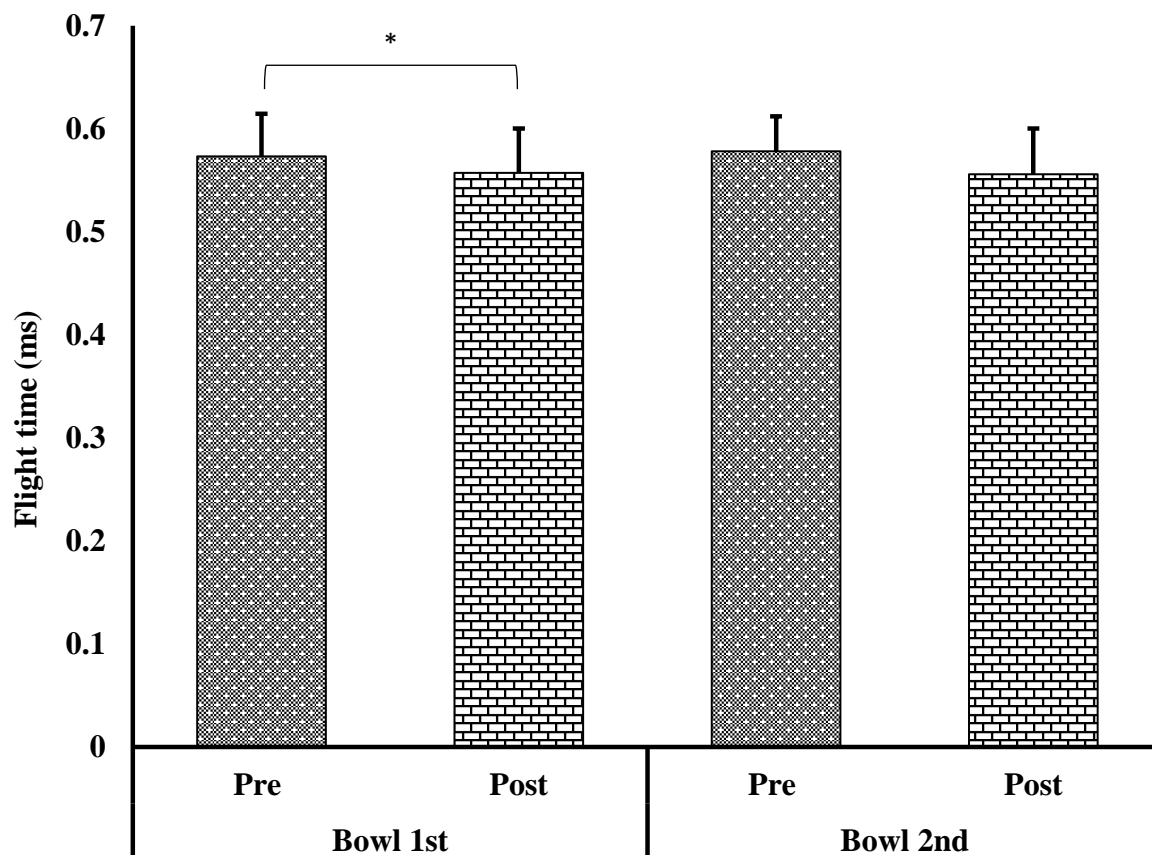


Figure 6.1. Flight time (ms) for counter movement jump as a result of bowling time.

*A significant difference from pre ($P \leq 0.05$). Data presented as mean \pm *SD*.

Moderate reductions in flight time between LOW – MODERATE bowling workloads were observed (Δ 30 ms; 90% CI 4 to 55; ES = 0.84 [moderate]; $P = 0.03$). Large reductions in flight time between LOW – HIGH bowling workloads were observed (Δ 43 ms; 90% CI 16 to 70; ES = 1.23 [large]; $P = 0.003$). Non-significant, small reductions in flight time were observed between MODERATE – HIGH bowling workloads (Δ 13 ms; 90% CI -10 to 37; ES = 0.36 [small]; ($P > 0.05$) (Figure 6.2).

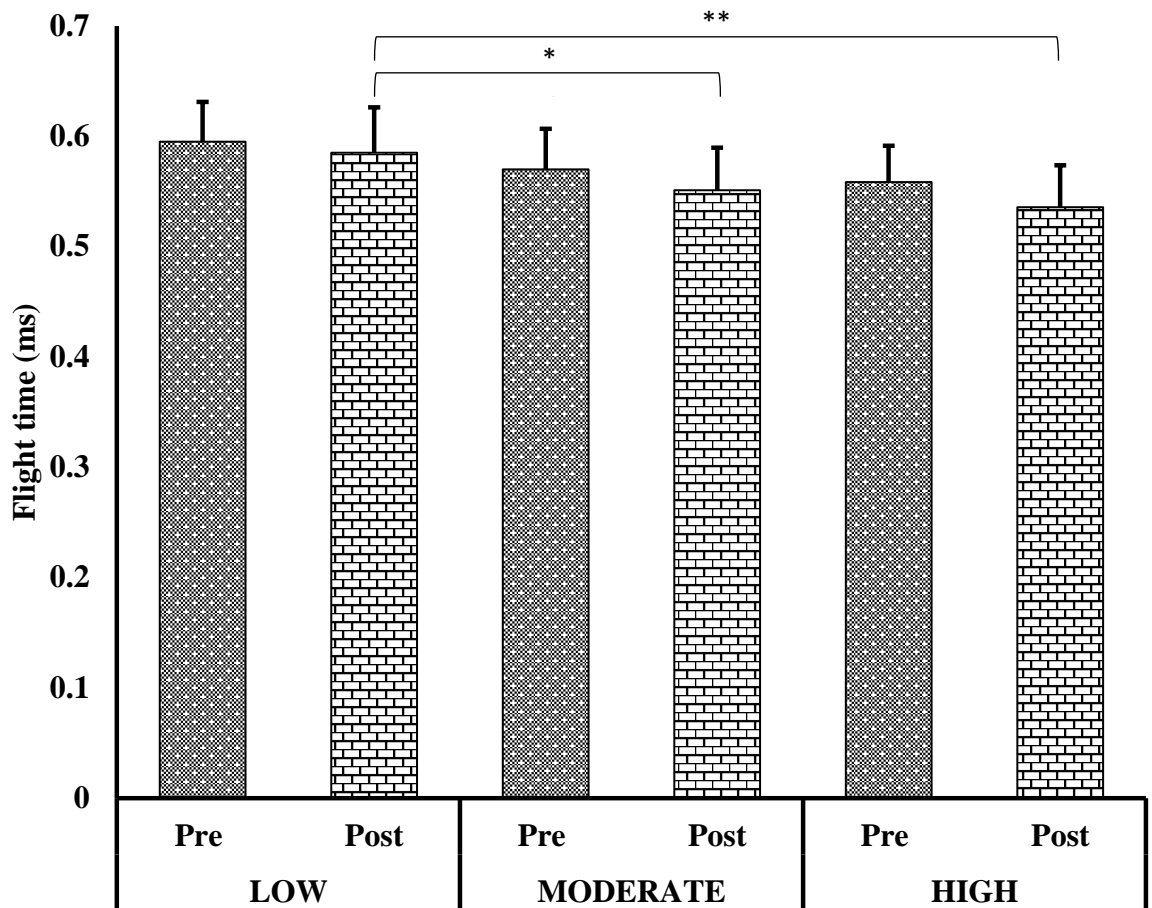


Figure 6.2. Flight time (ms) for countermovement jump as a result of bowling workload. * A significant difference from LOW to MODERATE ($P \leq 0.05$). ** A significant difference from LOW to HIGH ($P \leq 0.01$). Data presented as mean \pm SD.

Match Performance

The environmental conditions of all recorded matches were 17.7 ± 4.2 °C and 55.2 ± 11.3 % relative humidity. Mean match duration was 171.2 ± 35.0 min (20.4 %CV) with 44.2 ± 10.7 overs bowled (24.2 %CV). Individually, the mean bowling duration was 26.2 ± 11.1 min (42.4 %CV) with a spell length of 6.7 ± 2.8 overs (42.6 %CV). Absolute and relative descriptive data summarising movement categories contributing to total distance covered are reported in Table 6.1. This data is further categorised to include bowling only periods.

Table 6.1. Performance and subjective descriptive match data (mean \pm SD).

	Whole match	Bowling only period
MEMS parameters (ABS)		
TD (m)	9545 \pm 2448	3016 \pm 1243
LSRD (m)	8409 \pm 2111	2116 \pm 878
HSRD (m)	1132 \pm 452	898 \pm 381
TSD (m)	718 \pm 325	623 \pm 289
Total sprint number (<i>n</i>)	47 \pm 19	40 \pm 17
Peak speed (km·h ⁻¹)	32 \pm 3	31 \pm 3
PL (AU)	645 \pm 165	234 \pm 97
Subjective data		
RPE (AU)	4.6 \pm 1.4	N/A
MEMS parameters (REL)		
TD (m·min ⁻¹)	55.5 \pm 9.2	116.0 \pm 7.6
LSRD (m·min ⁻¹)	48.7 \pm 6.9	81.5 \pm 6.8
HSRD (m·min ⁻¹)	6.7 \pm 2.7	34.5 \pm 4.3
TSD (m·min ⁻¹)	4.3 \pm 2.1	23.8 \pm 5.3
Total sprint number (<i>n</i> ·min ⁻¹)	0.3 \pm 0.1	1.5 \pm 0.2
PL (AU·min ⁻¹)	3.8 \pm 0.7	9.0 \pm 0.6
Subjective data		
sRPE (AU)	816.0 \pm 298.1	N/A

TD = Total Distance; LSRD = Low-speed running distance (≤ 14.4 km·h⁻¹); HSRD = High-speed running distance (≥ 14.4 km·h⁻¹); TSD = Total sprint distance (≥ 18 km·h⁻¹); PL = PlayerLoad™; ABS = Absolute; REL = Relative

Correlations between Δ CMJ, MEMS match data and descriptive performance variables are reported in Table 6.2. This data is further presented to account for bowling workloads (Table 6.3.). Small, non-significant relationships were found among the ABS MEMS data and Δ CMJ. However, no REL data met the reportable correlation criteria. Small negative relationships were found between Δ CMJ and TD, LSRD, HSRD, TSD, number of sprints and PL, respectively. However, a small positive correlation was found in peak speed.

LOW Bowling Workloads. Small, non-significant relationships were found between Δ CMJ and MEMS match data. Small negative relationships were found between Δ CMJ and TD (ABS), LSRD (ABS & REL) and PL (ABS & REL) data, respectively. A small positive relationship was found between number of sprints (REL) and peak speed.

MODERATE Bowling Workloads. Small to moderate, non-significant relationships were found between Δ CMJ and MEMS match data. A small negative relationship was found between Δ CMJ and TD (ABS), LSRD (ABS) and PL (ABS). A small positive relationship was observed in HSRD (ABS & REL), number of sprints (REL) and PL (REL), respectively. A moderate negative relationship was found between Δ CMJ and TD (REL). A moderate positive relationship was found between Δ CMJ and peak speed, LSRD (REL) and TSD (REL), respectively.

HIGH Bowling Workloads. Small, non-significant relationships were found between Δ CMJ and MEMS match data. A small negative relationship between Δ CMJ and TD

(REL), LSRD (REL) and HSRD (REL) was observed. A similar-magnitude, positive relationship was found in TD (ABS), LSRD (ABS), HSRD, (ABS), peak speed and PL (ABS). Finally, a moderate negative relationship was found between Δ CMJ and TSD (REL) and number of sprints (REL).

Table 6.2. Correlations ($\pm 90\%$ CI) between Δ CMJ and MEMS parameters and descriptive performance variables across the whole match ($n = 57$) and also adjusted for LOW ($n = 12$), MODERATE ($n = 24$) and HIGH ($n = 18$) bowling workloads.

	Whole match	LOW (≤ 4 overs)	MODERATE (5-8 overs)	HIGH (9-12 overs)
MEMS parameters (ABS)				
TD (m)	-0.17 ^a (-0.38 to 0.05)	-0.18 ^a (-0.62 to 0.35)	-0.11 ^a (-0.44 to 0.24)	0.20 ^a (-0.22 to 0.56)
LSRD (m)	-0.18 ^a (-0.38 to 0.04)	-0.19 ^a (-0.63 to 0.34)	-0.13 ^a (-0.45 to 0.22)	0.20 ^a (-0.22 to 0.56)
HSRD (m)	-0.12 ^a (-0.33 to 0.10)	-0.06 ^a (-0.54 to 0.45)	0.12 ^a (-0.23 to 0.45)	0.15 ^a (-0.27 to 0.52)
TSD (m)	-0.13 ^a (-0.34 to 0.09)	-0.10 ^a (-0.57 to 0.42)	0.17 ^a (-0.19 to 0.49)	-0.08 ^a (-0.47 to 0.33)
Total sprint number (n)	-0.17 ^a (-0.38 to 0.05)	0.06 ^a (-0.45 to 0.54)	-0.07 ^a (-0.40 to 0.28)	0.01 ^a (-0.39 to 0.41)
Peak speed ($\text{km}\cdot\text{h}^{-1}$)	0.19 ^a (-0.03 to 0.39)	0.30 ^a (-0.23 to 0.70)	0.34 ^a (0.00 to 0.61)	0.28 ^a (-0.14 to 0.61)
PL (AU)	-0.21 ^a (-0.41 to 0.01)	-0.22 ^a (-0.65 to 0.31)	-0.27 ^a (-0.56 to 0.08)	0.25 ^a (-0.17 to 0.59)

Subjective data

RPE (AU)	-0.31* (-0.49 to -0.11)	0.06 ^a (-0.39 to 0.49)	-0.15 ^a (-0.45 to 0.18)	-0.52* (-0.76 to -0.16)
----------	--------------------------------	-----------------------------------	------------------------------------	--------------------------------

Descriptive data

Match duration (min)	-0.18 ^a (-0.37 to 0.03)	0.13 ^a (-0.33 to 0.54)	-0.32 ^a (-0.58 to 0.00)	0.43 ^a (0.05 to 0.70)
----------------------	------------------------------------	-----------------------------------	------------------------------------	----------------------------------

Match overs (<i>n</i>)	-0.18 ^a (-0.37 to 0.03)	0.15 ^a (-0.31 to 0.56)	-0.34 ^a (-0.60 to 0.02)	0.40 ^a (0.01 to 0.68)
--------------------------	------------------------------------	-----------------------------------	------------------------------------	----------------------------------

Individual bowling duration (min)	-0.15 ^a (-0.35 to 0.06)	-0.15 ^a (-0.56 to 0.31)	-0.04 ^a (-0.36 to 0.29)	-0.18 ^a (-0.53 to 0.23)
-----------------------------------	------------------------------------	------------------------------------	------------------------------------	------------------------------------

Individual overs bowled (<i>n</i>)	-0.25* (-0.44 to -0.04)	-0.28 ^a (-0.64 to 0.18)	0.03 ^a (-0.30 to 0.35)	-0.18 ^a (-0.53 to 0.23)
--------------------------------------	--------------------------------	------------------------------------	-----------------------------------	------------------------------------

Individual balls bowled (<i>n</i>)	-0.24 ^a (-0.43 to -0.03)	-0.31 ^a (-0.66 to 0.15)	0.13 ^a (-0.20 to 0.44)	-0.21 ^a (-0.55 to 0.20)
--------------------------------------	-------------------------------------	------------------------------------	-----------------------------------	------------------------------------

MEMS parameters (REL)

TD (m·min ⁻¹)	-0.03 ^a (-0.25 to 0.19)	-0.09 ^a (-0.56 to 0.43)	-0.34 ^a (-0.61 to 0.00)	-0.22 ^a (-0.57 to 0.20)
---------------------------	------------------------------------	------------------------------------	------------------------------------	------------------------------------

LSRD (m·min ⁻¹)	-0.05 ^a (-0.27 to 0.17)	-0.13 ^a (-0.59 to 0.39)	0.32 ^a (-0.03 to 0.6)	-0.17 ^a (-0.53 to 0.25)
-----------------------------	------------------------------------	------------------------------------	----------------------------------	------------------------------------

HSRD (m·min ⁻¹)	-0.02 ^a (-0.24 to 0.20)	0.06 ^a (-0.45 to 0.54)	0.28 ^a (-0.07 to 0.57)	-0.21 ^a (-0.56 to 0.21)
-----------------------------	------------------------------------	-----------------------------------	-----------------------------------	------------------------------------

TSD (m·min ⁻¹)	-0.04 ^a (-0.26 to 0.18)	-0.01 ^a (-0.51 to 0.49)	0.31 ^a (-0.04 to 0.59)	-0.35 ^a (-0.66 to 0.06)
----------------------------	------------------------------------	------------------------------------	-----------------------------------	------------------------------------

Total sprint number ($n \cdot \text{min}^{-1}$)	-0.10 ^a (-0.31 to 0.12)	0.17 ^a (-0.36 to 0.62)	0.27 ^a (-0.08 to 0.56)	-0.32 ^a (-0.64 to 0.09)
PL ($\text{AU} \cdot \text{min}^{-1}$)	-0.10 ^a (-0.31 to 0.12)	-0.15 ^a (-0.60 to 0.38)	0.17 ^a (-0.19 to 0.49)	-0.09 ^a (-0.47 to 0.32)

Subjective data

sRPE (AU)	-0.33** (-0.50 to -0.13)	0.07 ^a (-0.38 to 0.50)	-0.34 ^a (-0.60 to -0.02)	-0.30 ^a (-0.62 to 0.10)
-----------	---------------------------------	-----------------------------------	-------------------------------------	------------------------------------

TD = Total Distance; LSRD = Low-speed running distance ($\leq 14.4 \text{ km} \cdot \text{h}^{-1}$); HSRD = High-speed running distance ($\geq 14.4 \text{ km} \cdot \text{h}^{-1}$); TSD = Total sprint distance ($\geq 18 \text{ km} \cdot \text{h}^{-1}$); PL = PlayerLoadTM; ABS = Absolute; REL = Relative. * $P \leq 0.05$, ** $P \leq 0.01$. ^aNot significant.

Between-Match Variability

The %CVs (90% CI) and SWC of MEMS measures for both the whole match and the bowling only reference period are reported in Table 6.3. When comparisons are made between the absolute and relative whole match MEMS data, the results clearly demonstrate that, as movement speed classification increases, so does the degree of variability. The same trend is apparent with PL data (%CV ABS: 4.6 vs REL: 14.4). Total high-speed running distance (%CV ABS: 8.5 vs. REL: 30.1) showed lower variability compared to TSD (%CV ABS: 11.8 vs. REL: 55.4) and total sprint number (%CV ABS: 15.5 vs REL: 34.5), respectively. Much lower variability (%CV \leq 5) was observed in peak speed, TD and LSRD. Interestingly, however, with the exception of total number of sprints that increased (%CV ABS: 14.7 vs REL: 48.8), the bowling only MEMS data demonstrated that, as movement speed increases, the degree of variability decreases. This trend was especially apparent in TD (%CV ABS: 6.3 vs REL: 1.4), LSRD (%CV ABS: 6.6 vs REL: 1.9) and PL (%CV ABS: 9.4 vs REL: 3.3) respectively, where a threefold reduction was found.

Table 6.3. Between-match variation of MEMS parameters.

	Whole match		Bowling only period	
	CV (%; 90% CI)	SWC (%)	CV (%; 90% CI)	SWC (%)
MEMS parameters				
(ABS)				
TD (m)	3.3 (2.4 to 4.2)	6.0	6.3 (4.7 to 7.9)	9.9
LSRD (m)	3.3 (2.4 to 4.1)	5.9	6.6 (4.5 to 8.2)	9.9
HSRD (m)	8.5 (6.8 to 10.2)	11.8	7.8 (6.2 to 9.4)	10.4

TSD (m)	11.8 (9.6 to 14.0)	15.1	9.1 (7.3 to 10.9)	11.4
Total sprint number (<i>n</i>)	15.5 (13.8 to 17.2)	11.5	14.7 (13.0 to 16.4)	10.5
Peak speed (km·h ⁻¹)	2.9 (2.6 to 3.2)	2.0	3.0 (2.7 to 3.3)	2.0
PL (AU)	4.6 (3.7 to 5.5)	5.9	9.4 (7.8 to 11.0)	10.0

MEMS parameters

(REL)

TD (m·min ⁻¹)	4.4 (3.9 to 4.9)	3.5	1.4 (1.2 to 1.6)	1.3
LSRD (m·min ⁻¹)	3.9 (3.5 to 4.3)	3.0	1.9 (1.6 to 2.2)	1.7
HSRD (m·min ⁻¹)	30.1 (28.5 to 31.7)	10.7	3.5 (3.1 to 3.9)	2.5
TSD (m·min ⁻¹)	55.4 (53.3 to 57.5)	14.1	7.1 (6.4 to 7.8)	4.5
Total sprint number (<i>n</i> ·min ⁻¹)	34.5 (33.2 to 35.8)	9.1	45.8 (45.2 to 46.4)	3.7
PL (AU·min ⁻¹)	14.4 (13.8 to 15.0)	3.8	3.3 (3.1 to 3.5)	1.5

TD = Total Distance; LSRD = Low-speed running distance (≤ 14.4 km·h⁻¹); HSRD = High-speed running distance (≥ 14.4 km·h⁻¹); TSD = Total sprint distance (≥ 18 km·h⁻¹); PL = PlayerLoad™; ABS = Absolute; REL = Relative. %CV: coefficient of variation and 90% confidence interval; SWC%: smallest worthwhile change (0.2 x between subject standard deviation)

Rating of Perceived Exertion

The mean RPE and sRPE for each match was 4.6 ± 1.4 AU (30.4 %CV) and 816.0 ± 298.1 AU (36.5 %CV), respectively (Table 6.1.). There were no significant differences in RPE ($P > 0.05$), yet, a significant difference in sRPE was found ($P < 0.01$; Figure 6.3.). However, we noted that the significant differences were only present in those matches where playing time was considerably reduced, namely in match 8 ($\Delta 601.7$ AU; 66.7 to 1136.6; ES = 5.7 [very large]; $P = 0.03$) and in match 16 ($\Delta -662.5$ AU; -

1157.8 to -167.2; ES = 2.8 [very large]; $P = 0.004$), respectively. If both matches were omitted, no significant differences were found.

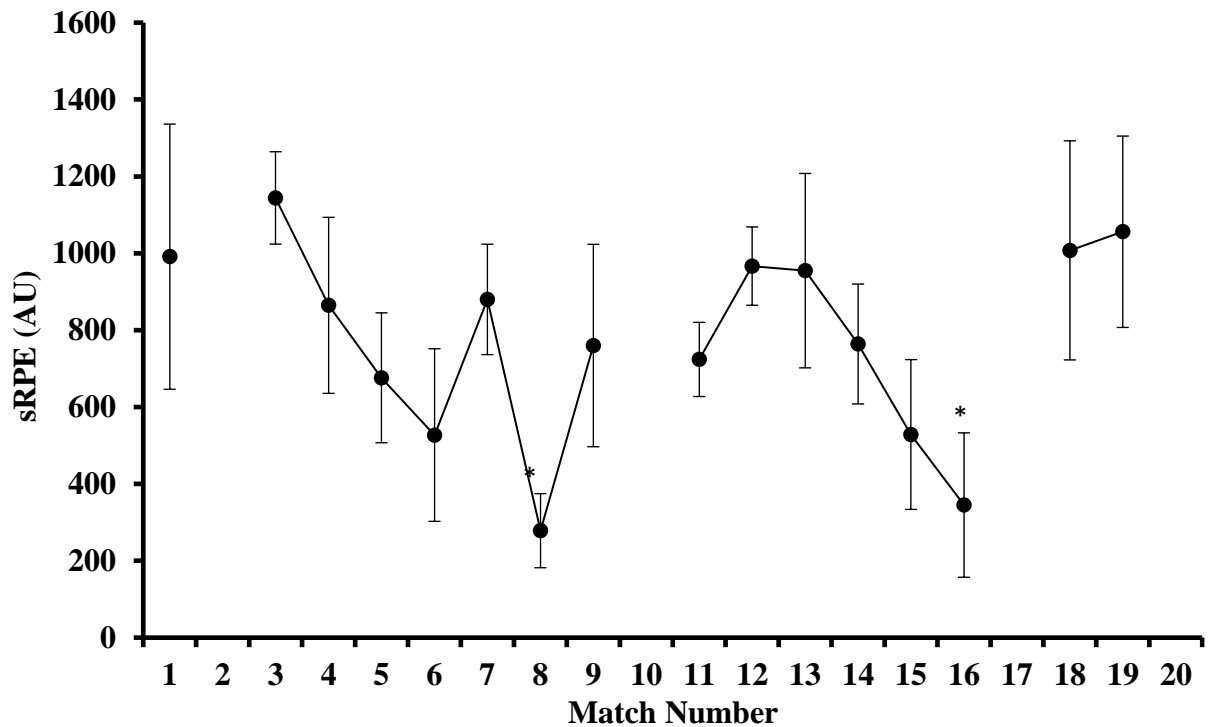


Figure 6.3. Session-RPE scores for each match throughout the season. *A significant difference from reduced match duration ($P \leq 0.05$). Data presented as mean \pm SD.

Moderate to very large, significant differences were observed in RPE between LOW – MODERATE (Δ 1.4 AU; 0.6 to 2.1; ES = 1.24 [large]; $P = 0.001$), LOW – HIGH (Δ 2.2 AU; 1.4 to 3.0; ES = 2.03 [very large]; $P < 0.01$) and MODERATE – HIGH (Δ 1.4 AU; 0.2 to 1.5; ES = 0.81 [moderate]; $P = 0.02$) bowling workloads, respectively. There were similar, significant differences observed in sRPE between LOW – MODERATE (Δ 231.1 AU; 71.8 to 390.5; ES = 0.86 [moderate]; $P = 0.01$), LOW – HIGH (Δ 472.3 AU; 298.7 to 646.0; ES = 2.07 [very large]; $P < 0.01$) and MODERATE – HIGH (Δ 241.2 AU; 90.2 to 392.3; ES = 1.08 [moderate]; $P = 0.004$) bowling workloads.

6.4. Discussion

Quantification of the presence and mechanisms of fatigue during limited overs cricket is of importance to coaching and support staff in order to develop training programs, manage player fatigue and plan effective recovery. Although previous research has determined fatigue and recovery in team sports (Andersson et al., 2008; Cormack et al., 2013; Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; R. D. Johnston et al., 2013; McLean et al., 2010; C. P. McLellan et al., 2011b; McNamara et al., 2013; Mooney et al., 2013; Ronglan et al., 2006; Thorlund et al., 2009; Wehbe et al., 2015), data presented in this experimental chapter is the first to report the NMF responses of fast bowlers during a season of limited overs one-day cricket, with special reference to bowling workload volumes. The main finding of this chapter confirms our hypotheses, that flight time was reduced significantly following an innings of limited overs one-day cricket. Moreover, the magnitude of the changes was significantly attenuated dependant on the bowling workload volume (LOW, MODERATE or HIGH). Furthermore, we aimed to determine if any specific MEMS parameters were associated with changes in NMF. These results suggest that fast bowlers experience acute NMF, which compromises important aspects of match physical performance.

Overall, a very large significant reduction in CMJ flight time was observed in fast bowlers following an innings of limited overs cricket (Δ 19 ms; ES = 5.4; P = 0.008). Interestingly, when this data were subsequently analysed to account for bowling time, significant reductions were only found in those matches where the team bowled first (Δ 19 ms; ES = 4.7; P = 0.05). Yet, a very large effect was found when the team bowled second (Δ 20 ms; ES = 4.9; P > 0.05). In general, the results from

this study broadly confirm the results of previous studies that have investigated the time-course change of CMJ data (flight time and force-power variables) during a competitive season (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010) or following a single match (Cormack, Newton, & McGuigan, 2008; C. P. McLellan et al., 2011b; Wehbe et al., 2015). Australian Rules Football (Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; Wehbe et al., 2015) and Rugby League research (McLean et al., 2010; C. P. McLellan et al., 2011b) have all shown that flight time was substantially reduced immediately post-match, which is in agreement with our findings. These studies also found notable reductions in flight time at subsequent time points (up to 48-h) following competition. However, this was not investigated in the present study. Although it has been argued (Cormack, Newton, & McGuigan, 2008; de Hoyo et al., 2016; Gathercole et al., 2015b) that some CMJ parameters (jump height and force-power variables) fail to provide a sensitive enough measure of short-term and residual NMF, the present findings indicate that changes in CMJ flight time appear to be a useful measure of NMF immediately following limited overs cricket.

A novel aspect of our analysis was to report on whether the different bowling workload volumes were associated with changes in CMJ performance and, thus, increased NMF. Moderate and large reductions were found in CMJ flight time in both LOW to MODERATE (Δ 30 ms; ES = 0.84; P = 0.03) and LOW to HIGH (Δ 43 ms; ES = 1.23; P = 0.003) workload groups, respectively. As might be expected, the greatest reduction in flight time is observed when bowlers were classified as bowling a HIGH volume. Interestingly, however, no significant differences were observed between MODERATE and HIGH bowling volumes. Such findings suggest that a “dose-response” relationship exists between bowling volume and NMF. Moreover, the

correlations presented show that the ABS measures of both external training load (TD, LSRD, HSRD, #sprints, PL) and descriptive match variables (match duration and overs) have a small to moderate influence on CMJ flight time, pre- to post-match, especially in those players who have a HIGH bowling workload. Research in Australian Rules Football (Cormack et al., 2013) has shown that players who covered greater distances on all GPS variables, were strongly associated with eliciting a higher level of muscle damage (creatine kinase; CK). Similarly, research from Rugby League has shown either a suppression in contractile force following competition, causally related to an increase in CK (C. P. McLellan et al., 2011b), or that, as match demands increase, muscular contractile force is suppressed (Duffield et al., 2012). While speculative, these findings support our reported associations between changes in CMJ performance and external training load data, suggesting that a selection of these variables may be used to indicate NMF in fast bowlers.

Important findings from this study are concerned with exploring relationships between the MEMS derived variables and the associated different bowling volumes and these changes in CMJ performance. There are a number of correlations evident. However, they are generally of negative association, small and variable. Despite this, it is interesting that some comparisons suggest a relationship between fast bowling workloads and increased NMF. For example, in the HIGH bowling workload group, some of the MEMS data (ABS; TD, LSRD, HSRD and PL) showed a small non-significant positive relationship ($r \geq 0.15$). This might suggest an association between greater distances covered and a greater reduction in CMJ flight time, where generally the opposite was found in the lower bowling volume groups. Interestingly, small to moderate positive non-significant relationships ($r \geq 0.28$) were found across all bowling workload groups between peak speed and an increased reduction in CMJ

flight time. Collectively, these findings further support the notion that high-speed running is more strongly associated with reductions in CMJ flight time and that neuromuscular status may have a delayed influence on performance. Surprisingly, however, aside from TD, only the MODERATE bowling workload showed a small to moderate non-significant positive relationship ($r \geq 0.17$) with relative MEMS data (i.e. $\text{m}\cdot\text{min}^{-1}$) and increased changes in CMJ performance. Uncertainty exists regarding the relationship between both subjective and descriptive match data and CMJ performance, with the majority negative and small. It is interesting to note however, that, in the HIGH bowling training load group, both match duration and total number of overs show moderate non-significant relationships ($r \geq 0.40$) with CMJ performance. Albeit speculative, these may be important variables as markers of competition and bowling training load in limited overs cricket. Although a number of correlations were present, predominantly negative and non-significant, it may be that increased monitoring at further subsequent time points (up to 48-h) may reveal more subtle variations in CMJ performance, resulting in further significant relationships (Cormack, Newton, McGuigan, & Cormie, 2008).

The MEMS match play data in this study provides conflicting results compared to the existing cricket literature (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009). When comparisons are made to the movement patterns of fast bowlers in professional one-day cricket, we found that the bowlers in this study covered less distance at all speed thresholds than those previously reported (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009). However, our results are in agreement with existing match variability data, that high-speed running parameters elicit the highest degree of variability between-matches (Petersen et al., 2010; Petersen, Pyne,

Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009) and descriptive match data, respectively. Specifically, our GPS descriptive data highlight that TD (9.5 km vs ≥ 13 km), HSRD (1.1 km vs 1.9 km) and TSD (0.7 km vs 1.2 km) are considerably less than those previously reported (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009). However, the descriptive match data relating to playing time (171 min vs 184 min) and overs bowled (7-overs vs 8-overs) are similar to those previously reported (Petersen et al., 2010; Petersen, Pyne, Portus, Karppinen, et al., 2009). Yet, this is somewhat to be expected, due to the bowling restrictions of one-day cricket. It is important to acknowledge that there is a notable difference in playing standard, despite the number of match observations similar to those of Petersen and colleagues (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011). Moreover, the results from this study provide further evidence to suggest an increase in running speed causes an increase in variation of distance covered at such speeds.

In contrast, TD, LSRD and PL were more stable between-matches for both whole match and bowling-only reference periods. The between-match variability for TD and LSRD is in agreement with that of Petersen and colleagues (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009), who concluded that TD was the parameter showing the least variability. When interpreting these findings, it is important to remember that fast bowlers can experience substantially different physical demands dependant on length of bowling spell or number of deliveries bowled. However, the observed low degree of variability of PL (ABS and REL) could provide an additional consideration when quantifying physical match demands.

By implementing the use of CV and SWC, a progressive magnitude-based statistical approach can be adopted to apply minimum thresholds (> 75% confidence) of significant changes in physical performance data, as discussed previously (Batterham & Hopkins, 2006; Hopkins et al., 2009; Kempton et al., 2014). Using this approach between-matches on selected MEMS data, we are able to show that a minimum change of 9.2 % is required to be confident that the change is real for TD (CV 3.3%; SWC 6.0%). When examining both HSRD (CV 8.5%; SWC 11.8 %) and PL (CV 4.6%; SWC 5.9%), the minimum threshold for a probable change was 20.5 % (HSRD) and 10.4% (PL), respectively. Likewise, when this statistical approach is applied to the bowling-only specific reference periods, the minimum changes for TD (6.9%), HSRD (16.4%) and PL (8.4%) are identified.

There were no significant differences in players' RPE during the entire season. However, a significant difference in sRPE was found. After further investigation, this difference was only found on two occasions where playing time was significantly reduced from the previous match. Similarly, our results show moderate to very large significant differences between RPE and sRPE when analysed according to bowling volumes. Our findings are in agreement with existing literature (Casamichana, Castellano, Calleja, Román, & Castagna, 2012; Impellizzeri et al., 2004), which has been shown to accurately reflect exercise intensity and MEMS parameters. Collectively, these findings are consistent with an altered sense of effort and support the use of sRPE as a tool that is sensitive enough to reflect variations in fast bowling training loads in one-day limited overs cricket.

In summary, this chapter examined both short-term NMF and the associated relationships with descriptive and MEMS training load measures, and the between-

match variability of MEMS characteristics during a season of professional OD cricket match play. Our results identified that, following an innings of OD cricket, fast bowlers demonstrated significant reductions in flight-time derived from a CMJ, which were magnified as a result of increased fast bowling workloads (≥ 4 -overs bowled), suggestive of short-term NMF. Secondly, and in line with our previous findings (see Chapter 5), we were able to reaffirm that global measures of performance TD and PL were relatively stable, yet, high-speed running still elicited the highest degree of between-match variability. Given the high degree of between-match variability and what may be considered a “dose-response” relationship with bowling workloads and NMF, further research is warranted to examine these relationships in a controlled environment. Therefore, by simulating spells of fast bowling and consequently removing the high degree of variability associated with match play, further research can investigate the short-term NMF associated with spells of fast bowling typically associated with limited overs OD cricket. Furthermore, we sought to explore similar “dose-response” relationships with markers of muscle damage and stress. Collectively, it is hoped that this will increase the overall understanding of match-related fatigue and the associated time-course responses relative to typical, limited overs fast bowling workloads.

7. Short-term Neuromuscular Fatigue and the Biochemical and Endocrine Responses Associated with an Indoor Bowling Simulation

7.1. Introduction

Cricket is an international team sport, where players are classified into specific roles including batsmen, fast bowlers, spin bowlers and wicket keepers, with fast bowlers typically accounting for three to five of the 11 players on each team (McNamara et al., 2015a; McNamara et al., 2013). Traditionally, cricketers would compete in multiday cricket and experience considerable breaks between matches and series (Orchard et al., 2015). However, further professionalization and the recent introduction of Twenty20 (T20) cricket has meant that cricketers now compete across three different match formats (multiday [MD; 4 or 5 day] and limited overs [one-day; 50-over & T20] cricket) (Hulin et al., 2014; McNamara et al., 2015a; McNamara et al., 2013; Petersen, Pyne, Portus, et al., 2011). Although fast bowlers compete across all competition formats, the competition demands are stochastic and are determined by both match type and match-play strategies adopted by the team captain (McNamara et al., 2015a).

These competition demands, coupled with the need to train at a high-intensity to elicit improvements in skill and physical fitness, may present time periods between matches and training inhibiting the restoration and recovery of important processes (e.g. psychological, NMF and muscle damage), leading to match-related fatigue (McLean et al., 2010; A. Scott et al., 2016). In light of the increased playing schedule and variability in both competition format and training loads, it is becoming increasingly important to understand the physiological time-course changes in response to fast bowling. This may not only reduce the likelihood of an unsuccessful performance, but also reduce the risk of injury (Andersson et al., 2008; Hulin et al.,

2014; Orchard et al., 2015; Orchard et al., 2010; Orchard et al., 2009). Therefore, the development and implementation of player-monitoring strategies that assess recovery from intense training and competition is of great interest to both practitioners and coaches, as such data may support important decisions on player involvement (A. Scott et al., 2016).

Fast bowling is a complex physically dynamic activity that requires technical and tactical skill (Minett et al., 2012b; Woolmer et al., 2009). Fast bowlers may be required to bowl for prolonged periods and could engage in up to 60 repeated upper- and lower-body high-intensity accelerations and decelerations separated by extended periods of lower intensity fielding activities during limited overs cricket (50-overs) (Minett et al., 2012a, 2012b; Orchard et al., 2009). Recent developments in TMA with wearable athlete-tracking MEMS now allow for routine analysis of the frequency and magnitude of movement in three dimensions (Boyd et al., 2011). Research incorporating MEMS technology has been used to highlight the fact that fast bowlers cover the greatest distances (~23 km during a full days play) at greater intensities (9% total time spent sprinting) than non-fast bowlers (McNamara et al., 2013; Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011), while also accumulating higher accelerometer loads (912 vs 679 AU), respectively (McNamara et al., 2013). The extent of exercise-induced muscle damage (EIMD) has been related to the intensity and duration of exercise (C. P. McLellan et al., 2011a; Urhausen & Kindermann, 2002). Therefore, as fast bowlers can be exposed to these repeated, prolonged eccentric muscle contraction forces during the fast bowling action, it is probable that this may result in EIMD (Noakes & Durandt, 2000; Twist & Eston, 2005). Moreover, failure to adequately account for these activities may greatly underestimate the physical demands of cricket fast bowling.

Effective monitoring strategies in cricket require tracking variables that are sensitive to physiological changes that accompany the stress of cricket fast bowling. Fatigue has often been described as an exercise-induced reduction in the maximal voluntary force-generating capacity (Cormack, Newton, & McGuigan, 2008; C. P. McLellan et al., 2011b; Mooney et al., 2013). A major area of interest for researchers and practitioners alike is the influence of fatigue (acute and chronic) on performance and, subsequently, the identification of reliable methods of assessment (Cormack, Newton, & McGuigan, 2008; Mooney et al., 2013). Traditionally, NMF was examined using isolated forms of isometric, concentric or eccentric movements (Gandevia, 2001; C. P. McLellan et al., 2011b). However, recent evidence now tends to suggest the use of movements that involve the SSC, providing a more specific examination of NMF (Cormack, Newton, McGuigan, & Cormie, 2008; Fowles, 2006; Komi, 2000; C. P. McLellan et al., 2011b). Moreover, the similarities in neuromuscular function between a CMJ and running suggest that the assessment of CMJ performance may be suitable for NMF monitoring in running-based sports (Wehbe et al., 2015). A number of researchers have found CMJ to be an objective marker of NMF for up to 48-h, following a single (Cormack, Newton, & McGuigan, 2008; Wehbe et al., 2015) or multitude of matches (Andersson et al., 2008; Cormack et al., 2013; Cormack, Newton, McGuigan, & Cormie, 2008; Duffield et al., 2012; McLean et al., 2010; Ronglan et al., 2006) across various team sports. Despite the current literature suggesting that significant NMF exists following team sport competition, currently, data pertaining to the NMF induced by cricket is limited and is typically cited as surrogate measures within the literature (Duffield et al., 2009; Minett et al., 2012a, 2012b). To date, McNamara et al. (2013) are the only researchers to describe the fatigue response of cricketers following competition and training. Data were collected

from academy professional fast bowlers ($n = 9$) and outfield players ($n = 17$) during a physical preparation (7-week) and 10-day intensified competition period (3 x 50-over; 2 x 2-day; 2 x T20 matches). Neuromuscular fatigue was assessed using a CMJ prior to competition (daily) and training (weekly), reporting unclear differences in CMJ flight time between the fast bowlers and non-fast bowling group in both the physical-preparation ($d = 0.34 \pm 0.47$) and competition phase ($d = 0.02 \pm 0.23$), respectively. Although only a secondary measure, Duffield et al. (2009) described the acute NMF response following a repeated spell of simulated fast bowling (2 x 6-overs; separated by 45-min walking). Neuromuscular fatigue was assessed (via CMJ) before and after each spell, with small, non-significant differences ($P = 0.6$; $d < 0.2$) found pre to post in spell one (mean \pm SD; 0.43 ± 0.06 vs 0.44 ± 0.07 m) and spell two (0.42 ± 0.07 vs 0.43 ± 0.07 m), respectively. Given these findings, it may be postulated that using a CMJ protocol to assess NMF in fast bowlers may not be warranted. However, it is possible that the competition demands experienced (McNamara et al., 2013) are not reflective of the professional adult game, which has been shown in Australian Rules Football (Burgess, Naughton, & Norton, 2012). Furthermore, it may be that fast bowlers are already conditioned to the prescribed simulated bowling workloads (Duffield et al., 2009). As such, by including biochemical and endocrine markers, it is possible that these may facilitate the identification of fatigue in cricket, specifically within fast bowlers.

As previously described, the demands of competitive cricket, including the fast bowling action, where bowlers are exposed to repeated, prolonged muscle actions, may collectively result in EIMD (Noakes & Durandt, 2000; Twist & Eston, 2005). Creatine kinase (CK) is an enzyme that is found in both the cytosol and mitochondria of the muscle and elevated concentrations in the blood can be used as an indirect

marker of EIMD (Baird et al., 2012; Clarkson & Ebbeling, 1988; C. P. McLellan et al., 2011b; A. Scott et al., 2016). The pattern of CK tends to mirror the mechanical-muscular strain of exercise in the preceding days, reacting to the intensity and volume of exercise (Urhausen & Kindermann, 2002). Consequently, indices of CK concentrations are now a common marker used to assess player fatigue and recovery status of prior exercise on subsequent performance (Russell et al., 2016). Previous research has explored numerous applications utilising plasma CK in the assessment of player fatigue and recovery status following training and competition, respectively (Hoffman et al., 2002; Hunkin et al., 2014; M. J. Johnston et al., 2016; R. D. Johnston et al., 2014; McLellan & Lovell, 2012; McLellan et al., 2010; C. P. McLellan et al., 2011a, 2011b; A. Scott et al., 2016). Collectively, these studies tend to show that CK concentrations typically peak at 24-h, remain elevated up to 48-h, prior to a subsequent return to a near basal concentration after 72- to 120-h, respectively. Despite the widespread application of measuring CK in team sports, data from cricket, specifically fast bowling, remains sparse. To date, Lombard et al. (2012) and Minett et al. (2012a, 2012b) are the only authors to detail the CK response following a spell(s) of fast bowling. In these studies, data were collected from professional state level fast bowlers (range: $n = 8$ to 10) who completed either a single (6- or 8-overs) or repeated spell of fast bowling over two consecutive days (day 1: 10- and day 2: 4-overs). The results from these studies appear to be inconclusive with Lombard et al. (2012) showing that an 8-over spell elicited significant differences and relative percentage increases in CK activity at 1 h ($P = 0.03$; 109%) and 24 h ($P = 0.04$; 77%) post bowling spell compared to baseline. Whereas Minett et al. (2012a, 2012b) reported no significant differences ($P > 0.05$), when extrapolating this data, both clearly show CK concentrations are elevated in response to 6- or 10-over spells, respectively. Moreover, the purpose of

these studies (Minett et al., 2012a, 2012b) was to explore the effectiveness of cooling and pre-cooling on fast bowling performance and therefore data was analysed appropriately to investigate the acute (pre – post) CK response following fast bowling. With the limited data available (Lombard et al., 2012), it could be suggested that a “dose-response” relationship may exist between fast bowling training loads and indirect markers of muscle damage. However, this warrants further investigation.

In addition to using CK as an indirect marker of muscle damage, it has been suggested that the concentration of nitrogenous waste in blood plasma, namely uric acid and urea, may be used as a marker of muscle protein breakdown (Bangsbo, 1994; Gleeson, 2002; Kindermann, 1986). As imbalances in protein, metabolic homeostasis is associated with tissue damage (Hoffman et al., 2002; Viru, 1987). Specifically, uric acid is related to the degradation of adenonucleotides, whereas urea is produced in the process of formation of ornithine from arginine after the introduction of ammonia (NH₃) groups into the urea cycle (Viru & Viru, 2001). The exercise-induced increased concentrations are indicative of enhanced protein catabolism and stimulated gluconeogenesis, resulting from higher training loads (Urhausen & Kindermann, 2002; Viru & Viru, 2001). Unfortunately, unlike the CK response to exercise, data pertaining to both uric acid and urea concentrations following team sport is limited (Andersson et al., 2008; Bangsbo, 1994; Hoffman et al., 2002). Although far from comprehensive, data from both men’s and women’s soccer show either a trend toward an increase in uric acid (Bangsbo, 1994), or a significant increase in both markers (UA 10.9 ± 2 %; urea 14.8 ± 2 %; $P < 0.05$) during a 90-min soccer match (Andersson et al., 2008).

Cortisol is considered an important stress hormone acting antagonistically with testosterone to mediate catabolic activity, increasing protein degradation and

decreasing protein synthesis in muscle cells (McLellan et al., 2010). The presence of cortisol is suggested as an indicator of the endocrine system's response to exercise and psychological stress (Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008). The use of salivary cortisol (sCort) concentrations is now commonly reported in team sports, owing largely to its non-invasive nature and to its being an effective indicator of plasma-free cortisol concentrations (Buchheit et al., 2013; Haneishi et al., 2007; Joyce & Lewindon, 2014). As a result, elevated sCort may be indicative of symptoms associated with overreaching and reflects the inability to recover following training and competition (Joyce & Lewindon, 2014). A relatively large body of literature has reported on the time-course of sCort recovery following team sport competition (Cormack, Newton, & McGuigan, 2008; Cormack, Newton, McGuigan, & Cormie, 2008; Haneishi et al., 2007; McLean et al., 2010). Coupled with the collection of both CMJ and biochemical data, these studies typically report that, immediately and 24-h post-match, sCort is significantly elevated, prior to returning to near baseline measures after 72-h. In addition to their quantification of NMF in junior academy cricketers, McNamara et al. (2013) also detailed the endocrine responses to both competition and training. Salivary cortisol data were collected weekly during the physical-preparation phase (training; $n = 7$) and every day during competition ($n = 7$). During both training ($d = -0.88 \pm 0.39$; 100%) and competition ($d = -0.39 \pm 0.30$; 85%) periods, sCort concentrations were greater in the fast bowlers than non-fast bowlers, respectively. These elevated cortisol concentrations shown across both periods are possibly linked to the increased training loads of fast bowlers. Thus, further research is required to examine, whether a “dose-response” relationship exists between fast bowling training loads and markers of fatigue and recovery following training and competition.

Although data tends to support the usefulness of CMJ protocols, biochemical (CK, UA, urea) and endocrine (sCort) markers of post-match NMF in other team sports, uncertainty still remains within cricket, especially for fast bowling. Moreover, although suggestive, it remains unclear whether incorporating the number of overs or deliveries bowled is of use to monitor performance and recovery in an applied setting. Therefore, the aim of this study was (a) to examine short-term NMF and the biochemical and endocrine responses associated with simulated fast bowling and (b) to determine the relationship between measures of training load (determined by MEMS) and post-simulation changes (from baseline) in CMJ performance, biochemical and endocrine concentrations. We hypothesised that longer bowling spells would result in substantial increases in NMF, EIMD and endocrine measures post-simulation.

7.2. Methods

Experimental Approach to the Problem

A randomised, repeated-measures cross-over design was used to examine the physical performance of senior club-level fast bowlers to determine NMF after four different bouts of simulated fast bowling and fielding activities. The biochemical, endocrine and perceptual well-being responses following the same bouts of simulated cricket fast bowling and fielding were also examined. In an attempt to overcome the typical match-to-match variability in locomotive movement patterns found during limited over cricket (Petersen, Portus, et al., 2009; Petersen et al., 2010), we examined the movement characteristics to a prescribed fast-bowling skills test (Cricket Australia-Australian Institute of Sport [CA-AIS]). Each session was separated by a minimum of seven days and comprised four different lengths of bowling spell, typically

experienced within limited overs, one-day cricket; 1) 4-over, 2) 6-over, 3) a randomised spell length (between 6- and 10-overs[RAND]) and 4) 10-over spell, respectively. Following each over, bowlers participated in simulated fielding activities and vice versa.

Performance during the modified CA-AIS fast-bowling skills test was measured using a portable MEMS device containing GPS and tri-axial accelerometer (100 Hz) technology. The accelerometer derived vector magnitude algorithm termed PL was selected based on previous team sport research (McLaren et al., 2016; Petersen, Portus, et al., 2009; Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009). Measurement of the dependent variable of flight time (FT; ms) during a CMJ was performed on an electronic jump mat pre and post the fast bowling simulation.

Plasma creatine kinase (CK), uric acid (UA) and urea were examined to indirectly assess the skeletal muscle damage in response to fast bowling. As CK, UA and urea are widely used as an indirect marker of skeletal muscle damage, assessing these responses allows for comparisons to be made with existing literature. Saliva cortisol (sCort) was examined to represent the primary catabolic endocrine measure associated with metabolism pre and post the fast bowling simulation. To examine the acute and short-term post-fast bowling simulation response of the dependent variables, CK, UA, urea and sCort were measured via venous blood and saliva samples, respectively.

Enhancing the understanding of player-movement characteristics, short-term NMF, EIMD and the endocrine response following typical spells of OD limited-overs fast-bowling are important considerations for practitioners and sport scientists when monitoring recovery and managing player preparation for subsequent matches.

Subjects

Eleven part-time senior club-level cricketers (mean \pm *SD*; age 27.3 ± 7.0 years; body mass 83.7 ± 11.6 kg; height 180.0 ± 6.3 cm) who reported \geq two training sessions and one competition day (Hunters ECB Yorkshire Premier League North) per week participated in this study. All participants were right-arm over, fast bowlers (run-up distance (mean \pm *SD*; 12.6 ± 2.4 m). For the purpose of this chapter, a fast bowler was defined as a bowler from whom the wicket keeper would normally stand back from the stumps, due to bowling speed (Dennis et al., 2004; Dennis et al., 2003; Dennis et al., 2005). All players were free from injury or any other medical condition that would have prohibited participation and adhered to a prescribed standardised pre-simulation routine (see Section 3. Subjects). Before participating in the study, all players were familiarised with all testing procedures during training sessions or non-competition matches. Written informed consent was obtained from each player and all players were free to withdraw from the study at any time. The Department of Sport, Health and Exercise Science Ethics Committee approved all experimental procedures and the study conformed to the declaration of Helsinki (World Medical, 2013).

Procedures

All data collection was completed during the in-season phase of competition at an indoor net facility. Following the standardised pre-simulation routine, a baseline measure of perceptual well-being was taken on arrival to the indoor net facility at 08:30 h. Saliva and blood samples were collected 30-min pre-simulation, within 30-min post-simulation and at 24-h into the post-simulation recovery period. The perceptual well-being, saliva and blood collection schedule is outlined in Table 7.1. Saliva and blood samples were collected daily between 08:30 – 09:00 h, with the

exception of the 30 min post-simulation samples that were collected between 10:00 – 12:30 h as dictated by the length of simulated overs bowled.

Table 7.1. Saliva and blood collection schedule; 24 h pre-simulation to 24 h post-simulation (spanning two consecutive days, typically separated by seven days).

Sample No.	1	2	3
Day	Day 1: Simulation	Day 1: Simulation	Day 2: Post simulation
Time (h)	-0.5 h Pre	≤ 0.5 h Post	24 h post
Sample	Saliva Blood	Saliva Blood	Saliva Blood
Perceptual measure	Wellness sRPE	Post-simulation (≤ 0.5 h) Wellness	

Players completed a standardised 10-min dynamic warm-up session similar to that previously described, including dynamic stretches followed by a series of different running patterns progressively increasing in intensity (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010; McNamara et al., 2013). Immediately following the standardised warm-up, baseline CMJ data was collected.

Players subsequently completed 10 practice deliveries, gradually increasing bowling speed to match intensity. Each one of the four different bowling spells was completed using a new 156 g four-piece cricket ball (County Supreme A, Readers, Northamptonshire, UK). Each bowling spell incorporated a modified version of the CA-AIS fast-bowling skills test (Duffield et al., 2009; Minett et al., 2012a, 2012b; M. Portus et al., 2010), whereby players completed a randomised assortment of short-, good-, and full-length deliveries on off-stump and leg-stump lines at match intensity, and in pairs (the eleventh player bowled with a partner not involved in the study). Total run-up and final 5 m run up speeds were recorded with a wireless infra-red timing system (Brower Timing Systems, Draper, USA) (see Chapter 3. Figure 3.2.).

Total distance was estimated during the fast bowling simulation based on the individual bowler's run-up distance and incorporating the standardised follow through distance (8.5 m). Bowling in pairs and alternating overs, players completed physical activities between overs to simulate fielding activities as previously reported (Duffield et al., 2009; Minett et al., 2012a, 2012b; M. Portus et al., 2010). Specifically, these activities included the completion of a 10 m walk on each delivery and a 20 m sprint on the second and fourth ball of each over. All procedures were repeated for each of the four fast-bowling simulations and players were asked to maintain a normal diet in the lead-up to and during the data collection period.

The Countermovement Jump

Before performing the CMJ test, subjects completed a standardised 10-min dynamic warm-up similar to that previously described, including dynamic stretches followed by a series of different running patterns progressively increasing in intensity (Cormack, Newton, McGuigan, & Cormie, 2008; McLean et al., 2010; McNamara et al., 2013). Subjects then performed three submaximal practice CMJs before the measurement trial. Each subject then performed three CMJs, with 3 min of rest between each CMJ at a standard time between 09:00 – 09:30 h, prior to the fast bowling simulation. All CMJs were performed with hands held firmly on the hips and subjects were instructed to jump as high as possible. All jumps were performed at a self-selected countermovement depth (Cormack, Newton, McGuigan, & Cormie, 2008; McNamara et al., 2013). The best result from the three CMJs was used for analysis. The CMJ was performed on a commercially available electronic jump mat (Smart Jump, Fusion Sport, Queensland, Australia) operated by manufacturer software

(Smart Speed, Fusion Sport, Queensland, Australia) to calculate flight time (FT [ms]). Coefficient of variation (CV) as a percentage of the FT was 2.4%.

Training Load

For the duration of the protocol, heart rate and PL data were recorded via an individual MEMS device encased within a neoprene vest, which housed the device between the scapulae. Manufacturer-derived heart rate exertion index (HREI) was used to calculate the internal training load. Heart rate was collected during all experimental procedures (every 5 s; T31, Polar Electro Oy, Finland) transmitting continuously to the MEMS device (MinimaxX Team Sports v2.5, Catapult Innovations, Melbourne, Australia; mass 64.5 g; size 0.9 x 0.5 x 0.2 cm). This method follows the same principles as Edwards (1994), utilising arbitrary exponential weighting factors:

$$\begin{aligned} & (\text{Duration in Zone 1} \times 1) + (\text{Duration in Zone 2} \times 1.20) + (\text{Duration in Zone 3} \times 1.50) \\ & + (\text{Duration in Zone 4} \times 2.20) + (\text{Duration in Zone 5} \times 4.50) \end{aligned}$$

Where Zone 1 = 50-60% of HR_{\max} , Zone 2 = 60-70% of HR_{\max} , Zone 3 = 70-80% of HR_{\max} , Zone 4 = 80-90% of HR_{\max} and Zone 5 = 90-100% of HR_{\max} .

The MEMS device contained a tri-axial piezoelectric linear accelerometer (Kionix, KXP94) sampling at a frequency of 100 Hz. As recommended, each bowler wore the same MEMS device throughout all testing procedures to avoid interunit error (Jennings et al., 2010b; R. J. Johnston et al., 2015). Approximately 30-min before each trial, the MEMS device was switched on and accelerometers calibrated according to the manufacturer's instructions. The units were switched off immediately after each trial. The MEMS units used in this study have been shown to be a valid and reliable

measure of movement patterns in cricket (Petersen, Pyne, Portus, & Dawson, 2009). PlayerLoad™ expressed in arbitrary units (AU) was calculated in Sprint (Catapult Innovations, Melbourne, Australia), which is a modified vector magnitude expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in all three vectors (X, Y and Z axis) divided by 100, as previously described (Boyd et al., 2011; Montgomery et al., 2010). These MEMS devices have provided a highly reliable (CV% < 2) measure of PL in laboratory-based simulations (Boyd et al., 2011) and, more recently, during simulated team sport play (Barrett et al., 2015).

Data were downloaded post-match using Sprint (V5.1.0, Catapult Innovations, Melbourne, Australia) software and subsequently analysed and processed by applying the proprietary intelligent motion filter. Each file was subsequently split into specific reference periods, which allowed bowling only profiles to be established (see Section 3. *Cropping of data*). All training load variables were represented in absolute (ABS) and relative terms (REL; i.e. PL·min⁻¹), indicative of volume and intensity. Relative measures were calculated as the absolute measure divided by the duration of the protocol. A total of 44 files was analysed.

Muscle Damage

Indirect measures of muscle damage were assessed using venous blood drawn daily between 8:30 – 9:00 h, 30 min and 24 h post simulation, respectively. All blood samples were drawn directly into a 6 mL lithium heparin vacutainer (Greiner Bio-One Ltd, Stonehouse, UK) using standard venepuncture techniques and centrifuged (Thermo Scientific Hereaus, Labofuge 400 R, Fisher Scientific UK, Loughborough, UK) at 2300 rpm for 10-min at 4°C, and separated plasma was pipetted off and stored

in Eppendorf tubes (Sarstedt, Numbrecht, Germany) at -80°C until analysis. Blood samples were collected from players simultaneously at the time of saliva sample collection. Plasma CK ($\text{U}\cdot\text{L}^{-1}$), UA ($\mu\text{mol}\cdot\text{L}^{-1}$) and urea ($\text{mmol}\cdot\text{L}^{-1}$) were measured *ex vivo* using the ABX Pentra 400 auto-analyser system (Horiba, Montpellier, France). Each parameter was subjected to the necessary calibration and quality control methods (ABX Pentra Multical, ABX Pentra CK Control, ABX Pentra N Control and ABX Pentra P Control) as instructed by the manufacturer. The CV for these assays was as follows: CK 9.1%; UA 2.4 % and urea 4.0%, respectively.

Endocrine Measures

Saliva samples were collected daily between 8:30 – 9:00 h, 30 min and 24 h post simulation, using a 10 mm x 38 mm salivary oral swab (Salivette, Sarstedt, Numbrecht, Germany) in order to determine the sCort response to simulated fast bowling. Players were instructed to gently chew the swab for 1 minute and then place the swab in the storage cryovial. Players were requested to avoid the ingestion of food and fluids other than water in the 60 min before providing each sample and to refrain from brushing their teeth 2 h before each saliva sample-collection session. Players were instructed to wait 10 min after their last consumption of water before commencing the sample-collection process. All saliva samples were centrifuged at 2300 rpm for 2 min at 4°C . Saliva was pipetted off and stored in Eppendorf tubes (Sarstedt, Numbrecht, Germany) at -80°C until analysis.

Salivary cortisol (ng·ml) samples were analysed in duplicate via a commercially available Enzyme-Linked Immunosorbent Assay (ELISA, Abcam, ab154996, Abcam, Cambridge, UK) using a microplate reader (Tecan Infinite M200 Pro plate reader, Tecan, Männedorf, Switzerland). Standard curves were constructed

as per the manufacturer's instructions and commercially available standards (Abcam, Cambridge, UK). Cortisol sensitivity was 0.12 ng·ml with an average intra-assay CV of $\leq 10\%$. All samples were analysed in the same series to avoid inter-assay variability.

Perceptual Well-Being

Subjective perceptions of well-being were measured using a previously used psychological questionnaire (R. D. Johnston et al., 2013; McLean et al., 2010) (see Appendix B) based on the original recommendations of Hooper and Mackinnon (1995). The questionnaire rated feelings of fatigue, sleep quality, general muscle soreness, stress levels and mood on a 1-5 Likert scale. Each score was summated to provide an overall well-being score, with the suggestion that, the higher the score, the greater the well-being. The questionnaire was completed upon arrival to the indoor net facility prior to commencing the trial and 24 h post simulation (08:30 h). Similar scales have been shown to have good reliability and validity (De Vries, Michielsen, & Van Heck, 2003).

Session Rating of Perceived Exertion

Rating of perceived exertion (RPE) was obtained within 30 min after each trial using a modified RPE scale (Foster et al., 2001). Match load was calculated by multiplying the RPE score with playing minutes (sRPE).

Statistical Analyses

The differences in neuromuscular, psycho-biological fatigue and MEMS performance data were determined between simulated fast bowling volumes using traditional significance testing combined with magnitude-based inferences (Batterham &

Hopkins, 2006; Cohen, 2013; R. D. Johnston et al., 2013). All data were confirmed as being normally distributed and therefore presented as the mean \pm *SD*. A repeated measures (time * load) analysis of variance was used to determine the statistical significance of bowling volume on CMJ performance (measured by flight time [ms]), muscle damage, perceived wellness and sRPE. If significant main effects were found, a Bonferroni post hoc test was performed to locate the differences. The level for statistical significance was set at $P \leq 0.05$. Data are reported as the mean difference and 90% confidence interval (90% CI) as markers of the uncertainty of the estimates (McLaren et al., 2016). Cohen's *d* effect size (ES) statistic was used to show the magnitude of each effect (Cohen, 2013). Effect sizes were classified as: 0.00-0.19, 0.20-0.59, 0.60-1.19, 1.20-1.99 and ≥ 2.00 and were considered trivial, small, moderate, large and very large, respectively (Hopkins et al., 2009).

Pearson's product-moment correlations (*r*) were calculated to assess relationships between training load and subjective data collected from the CA-AIS fast bowling skills test and the change (relative to baseline; Δ [pre_post]; Δ 24 [pre 24 h post]) in CMJ, biochemical and endocrine measures. Further correlations were calculated to assess the same relationships after controlling for bowling volume. The following criteria were adopted to identify the magnitude of the correlation <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 $0.9 - 0.99$, nearly perfect (Hopkins et al., 2009). Correlations of ≤ 0.1 have not been reported. All statistical analyses were performed using SPSS (IBM SPSS Statistics, v.23, IBM Corp., Armonk, NY, USA.).

7.3. Results

Neuromuscular Fatigue

Small to moderate, significant reductions in CMJ flight time pre to post (Δ 21 ms; 90% CI 17 to 25; ES = 0.53 [moderate]; $P < 0.01$) and pre to 24 h post (Δ 8 ms; 90% CI 4 to 13; ES = 0.20 [small]; $P = 0.001$) were found following the CA-AIS fast bowling simulation. A trivial, significant difference was found in CMJ flight time post to 24 h post simulation (Δ -12 ms; 90% CI -8 to -17; ES = -0.30 [trivial]; $P < 0.01$). Figure 7.1. illustrates the individual CMJ responses following each CA-AIS fast bowling trial. Specifically, during the simulated 4-over spell, a small significant reduction was found in CMJ flight time pre to post (Δ 19 ms; 90% CI 12 to 26; ES = 0.49 [small]; $P < 0.01$). Trivial, non-significant differences were found in both CMJ flight time pre to 24 h (Δ 5 ms; 90% CI -8 to 17; ES = 0.13 [trivial]; $P = 1.00$) and post to 24 h post simulation (Δ -14 ms; 90% CI -1 to -27; ES = -0.35 [trivial]; $P = 0.06$), respectively. During the simulated 6-over spell, a moderate significant reduction was observed for CMJ flight time pre to post (Δ 26 ms; 90% CI 17 to 34; ES = 0.63 [moderate]; $P < 0.01$). A small non-significant difference was found in CMJ flight time pre to 24 h post (Δ 9 ms; 90% CI -4 to 22; ES = 0.20 [small]; $P = 0.35$), yet, a trivial significant difference was found between CMJ flight time post to 24 h post simulation (Δ -17 ms; 90% CI -9 to -25; ES = -0.39 [trivial]; $P = 0.002$), respectively. Following the simulated RAND-over spell, a small significant reduction was found in CMJ flight time pre to post (Δ 15 ms; 90% CI 6 to 24; ES = 0.31 [small]; $P = 0.005$). Trivial, non-significant differences were found in both CMJ flight time pre to 24 h (Δ 7 ms; 90% CI 0 to 13; ES = 0.16 [trivial]; $P = 0.08$) and post to 24 h post simulation (Δ -9 ms; 90% CI -19 to 2; ES = -0.20 [trivial]; $P = 0.23$), respectively. During the simulated 10-over spell, a moderate significant reduction was observed for CMJ flight time pre to post (Δ 24 ms; 90% CI 12 to 37; ES = 0.60 [moderate]; $P = 0.002$). A small significant difference was found in CMJ flight time pre to 24 h post (Δ 14 ms; 90% CI

3 to 24; ES = 0.34 [small]; $P = 0.03$), and a trivial significant difference was found between CMJ flight time post to 24 h post simulation ($\Delta -10$ ms; 90% CI -5 to -16; ES = -0.26 [trivial]; $P = 0.004$), respectively.

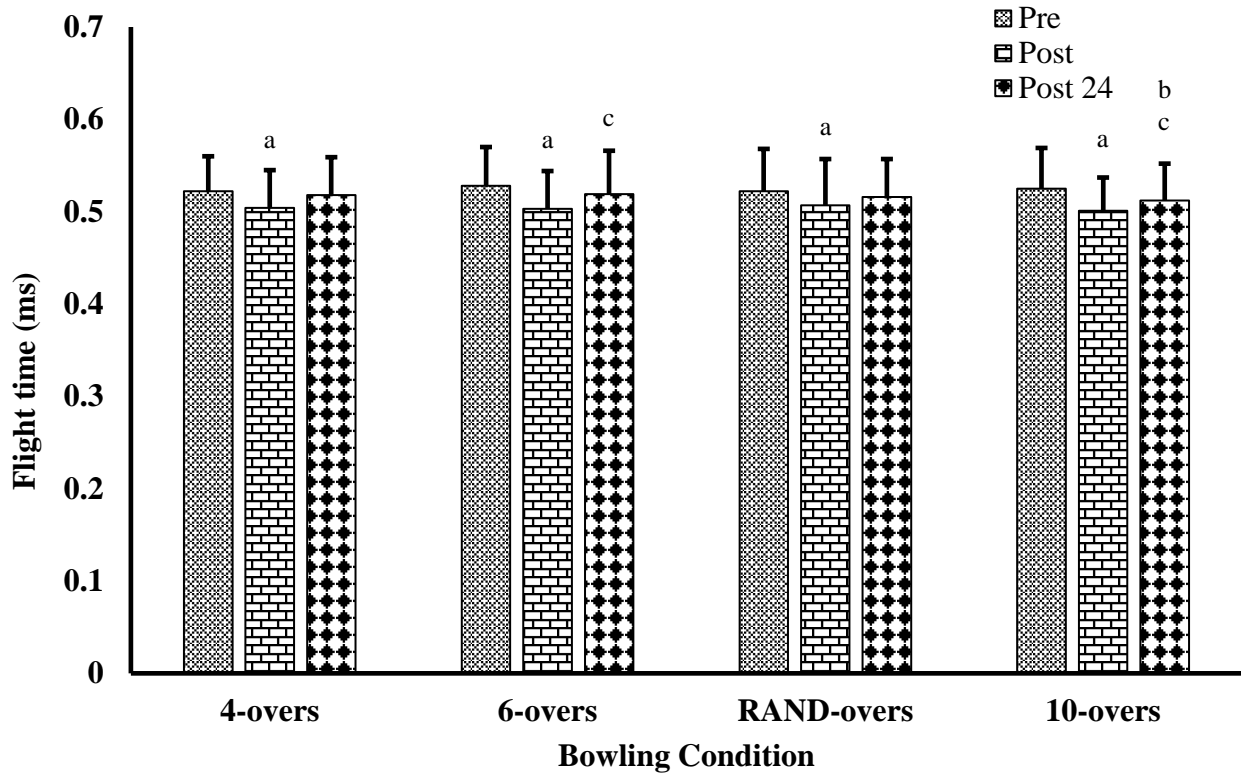


Figure 7.1. Flight time (ms) for counter movement jump data as a result of simulated fast bowling; a: significant difference from pre to post ($P \leq 0.01$); b: significant difference from pre to post 24 h ($P \leq 0.05$); c: significant difference from post to 24 h post ($P \leq 0.05$). Data presented as mean \pm SD.

Simulation Performance

The environmental conditions of all recorded CA-AIS fast bowling simulation sessions were 20.9 ± 1.8 °C and 58.8 ± 11.4 % RH. There was a significant main effect between simulation duration of each of the four trials ($P < 0.01$). The mean simulation duration for each trial was; 4-overs 34.9 ± 2.5 min (7.2 %CV), 6-overs 51.3 ± 6.1 min (11.9 %CV), RAND-overs 66.7 ± 8.3 min (12.4 %CV) and 10-overs 83.9 ± 4.2 min

(5.0 %CV), respectively. The run-up speeds, internal and external training load characteristics and subjective data obtained whilst performing the CA-AIS fast bowling simulation are reported in Table 7.2.

Run-up

There were no significant differences found between the mean total run-up speed ($P = 0.54$) nor final 5 m run-up speed ($P = 0.07$) across each trial, respectively. There was a significant main effect of estimated TD covered between all bowling conditions ($P \leq 0.01$). Post hoc analysis showed large to very large significant increases in the estimated TD covered between all bowling trials (range ES = 1.47 to 7.47; $P \leq 0.01$). No significant differences were found between all bowling trials for estimated relative TD covered ($P = 0.31$).

MEMS parameters

There was a significant main effect of accumulated PL between bowling trials ($P \leq 0.01$), with post hoc analysis showing very large significant differences between all bowling trials (range ES = 2.21 to 6.97; $P \leq 0.01$). However, no significant differences were found between relative PL and bowling trial ($P = 0.72$). There were no significant differences found between HR ($P = 0.61$) or HR_{peak} ($P = 0.89$), respectively. A significant main effect between fast bowling trial and HREI was found ($P \leq 0.01$). Specifically, large to very large significant differences were found between the 4- and 6-over ($\Delta 25.0$ AU; 90% CI 4 to 46; ES = 1.69 [large]; $P = 0.03$), 4- and RAND-over ($\Delta 45.8$ AU; 90% CI 25 to 67; ES = 2.06 [very large]; $P \leq 0.01$) and 4- and 10-over trials ($\Delta 72.0$ AU; 90% CI 51 to 93; ES = 3.74 [very large]; $P \leq 0.01$), respectively. Further, very large to moderate significant differences were found between 6- and 10-

over (Δ 47.0 AU; 90% CI 26 to 68; ES = 2.92 [very large]; $P \leq 0.01$) and RAND- and 10-over (Δ 26.2 AU; 90% CI 5 to 47; ES = 1.11 [moderate]; $P = 0.02$) bowling trials.

Table 7.2. Performance and subjective CA-AIS fast bowling simulation data in all conditions (mean \pm SD).

	4-overs	6-overs	RAND-overs	10-overs
Descriptive				
Deliveries (<i>n</i>)	24 \pm 0	36 \pm 0	48.2 \pm 6.0	60 \pm 0
Run-up				
Mean speed (km·h ⁻¹)	15.2 \pm 2.1	15.3 \pm 2.0	15.4 \pm 1.9	15.3 \pm 2.1
Final 5-m speed (km·h ⁻¹)	16.1 \pm 2.6	16.6 \pm 2.5	16.4 \pm 2.1	16.4 \pm 2.5
Estimated TD (m)	984.8 \pm 114.6	1482.0 \pm 170.0	1986.3 \pm 339.0	2470.1 \pm 283.3
Estimated relative TD (m·min ⁻¹)	68.0 \pm 8.5	71.9 \pm 6.0	73.8 \pm 6.1	71.2 \pm 8.1
MEMS parameters				
PL (AU)	171.3 \pm 20.7	265.4 \pm 26.1	388.0 \pm 35.4	439.6 \pm 56.5
Relative PL (AU·min ⁻¹)	4.9 \pm 0.7	5.2 \pm 0.7	5.1 \pm 0.7	5.3 \pm 0.8
HR (b·min ⁻¹)	129 \pm 15	135 \pm 11	127 \pm 13	131 \pm 13
HR _{peak} (b·min ⁻¹)	167 \pm 12	169 \pm 11	166 \pm 12	169 \pm 8

HREI (AU)	55.5 ± 17.8	80.5 ± 11.5	101.3 ± 26.4	127.5 ± 20.6
Subjective				
Perceptual well-being (AU; Pre)	17.8 ± 1.4	18.3 ± 2.3	18.4 ± 1.3	17.8 ± 2.0
Perceptual well-being (AU; Post 24 h)	16.5 ± 2.9	15.5 ± 3.3	15.9 ± 2.3	15.5 ± 1.8
RPE (AU)	3.0 ± 0.6	4.0 ± 0.7	6.2 ± 1.2	5.3 ± 1.4
sRPE (AU)	105.5 ± 25.9	207.2 ± 53.7	355.6 ± 110.0	501.5 ± 142.8

TD = Total distance; PL = PlayerLoad™; HR = Heart-rate; HREI = Heart-rate exertion index; RPE = Rating of Perceived Exertion; sRPE = session Rating of Perceived Exertion.

Biochemical and Endocrine Measures

Table 7.3. shows the descriptive biochemical and endocrine concentrations spanning the three data collection time points (pre [-0.5 h] and post [+0.5 h; +24 h]) for each of the four CA-AIS fast bowling simulated over trials.

Plasma Creatine kinase (CK) concentrations

There was a trivial, significant increase in plasma CK concentration found pre to post simulation (Δ 110.2 U·L⁻¹; 90% CI 59.8 to 160.6; ES = 0.13 [trivial]; $P < 0.01$). Trivial non-significant differences were found in CK concentrations at both pre to 24 h post (Δ 124.3 U·L⁻¹; 90% CI 31.6 to 280.2; ES = 0.17 [trivial]; $P = 0.26$) and post to 24 h post simulation (Δ 14.1 U·L⁻¹; 90% CI -137.6 to 165.8; ES = 0.02 [trivial]; $P = 1.00$), respectively. Figure 7.2. illustrates the individual CK responses following each CA-AIS fast bowling trial. Specifically, as a result of bowling 6-overs, a small significant increase in CK concentration was found pre to post simulation (Δ 93 U·L⁻¹; 90% CI 21 to 165; ES = 0.28 [small]; $P = 0.031$). A small significant increase in CK concentration was observed in the RAND-over trial pre to post simulation (Δ 72 U·L⁻¹; 90% CI 29 to 115; ES = 0.31 [small]; $P = 0.006$). Small to moderate significant increases in CK concentration were found as a result of the 10-over bowling trial in both pre to 24 h post (Δ 495 U·L⁻¹; 90% CI 80 to 910; ES = 0.67 [moderate]; $P = 0.047$) and post to 24 h post (Δ 284 U·L⁻¹; 90% CI 52 to 516; ES = 0.33 [small]; $P = 0.042$), respectively. There were no significant differences ($P \geq 0.05$) between CK concentrations and the time-course of recovery following 4-overs in the CA-AIS fast bowling trial.

Table 7.3. Biochemical and endocrine concentrations across the time-course of recovery following CA-AIS fast bowling simulation in all conditions (mean \pm *SD*).

	4-overs	6-overs	RAND-overs	10-overs
Pre-simulation				
CK (U·L ⁻¹)	901.8 \pm 1549.5	270.3 \pm 310.9	230.5 \pm 203.7	357.3 \pm 528.5
UA (μ mol·L ⁻¹)	369.4 \pm 41.7	358.1 \pm 40.8	335.7 \pm 38.5	337.1 \pm 21.3
Urea (mmol·L ⁻¹)	5.2 \pm 1.3	4.9 \pm 1.4	4.0 \pm 0.3	4.4 \pm 1.1
sCort (ng·ml)	23.8 \pm 14.9	6.1 \pm 3.1	9.9 \pm 3.9	23.0 \pm 14.6
Post-simulation				
CK (U·L ⁻¹)	966.1 \pm 1626.8	363.3 \pm 355.3	302.7 \pm 257.5	568.6 \pm 780.7
UA (μ mol·L ⁻¹)	377.6 \pm 45.7	379.0 \pm 50.7	341.2 \pm 34.5	350.0 \pm 27.2
Urea (mmol·L ⁻¹)	5.2 \pm 1.3	5.1 \pm 1.3	4.1 \pm 0.4	4.6 \pm 1.1
sCort (ng·ml)	11.2 \pm 5.5	4.9 \pm 2.2	4.9 \pm 3.4	3.7 \pm 1.4

24-hour post-simulation

CK (U·L ⁻¹)	607.9 ± 863.2	464.4 ± 334.3	332.5 ± 184.3	852.2 ± 955.1
UA (μmol·L ⁻¹)	382.7 ± 40.8	372.3 ± 56.4	336.1 ± 44.2	356.7 ± 27.0
Urea (mmol·L ⁻¹)	4.8 ± 1.0	5.1 ± 1.1	4.3 ± 0.9	4.5 ± 1.0
sCort (ng·ml)	15.2 ± 16.7	9.4 ± 4.4	9.2 ± 3.4	4.2 ± 2.1

CK = creatine kinase; UA = uric acid; sCort = salivary cortisol.

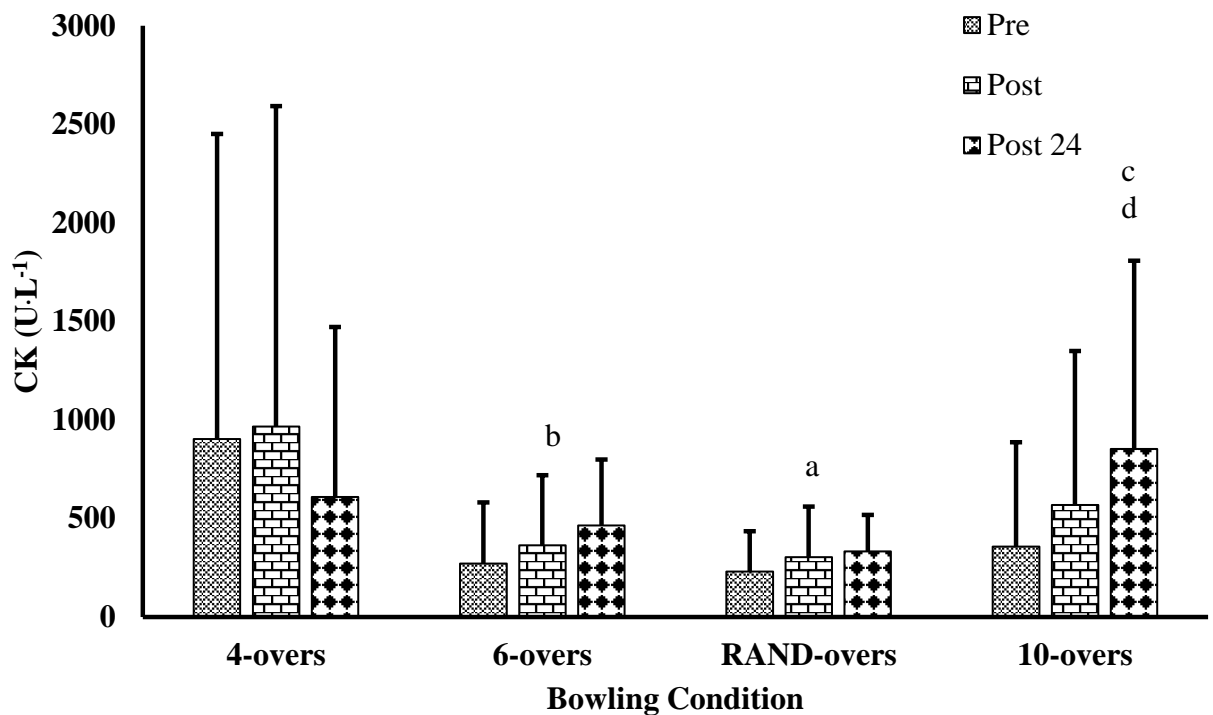


Figure 7.2. Plasma creatine kinase (CK) concentration (U·L⁻¹) as a result of simulated fast bowling; a: significant difference from pre to post ($P \leq 0.01$); b: significant difference from pre to post ($P \leq 0.05$); c: significant difference from pre to post 24 h ($P \leq 0.05$); d: significant difference from post to 24 h post ($P \leq 0.05$). Data presented as mean \pm SD.

Plasma uric acid (UA) concentrations

There were small, significant increases in plasma UA concentrations at both pre to post ($\Delta 11.9 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI 6.2 to 17.5; ES = 0.30 [small]; $P < 0.01$) and pre to 24 h post ($\Delta 11.9 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI 2.2 to 21.5; ES = 0.29 [small]; $P = 0.03$) fast bowling simulation, respectively. A trivial, non-significant difference in UA concentration was found between post and 24 h post simulation ($\Delta 0.01 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI -8.3 to 8.3; ES = 0.00 [trivial]; $P = 1.00$). Figure 7.3. illustrates the individual UA responses following

each CA-AIS fast bowling trial. Specifically, as a result of bowling 6-overs, a small significant increase in UA concentration was found pre to post simulation ($\Delta 21 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI 4 to 38; ES = 0.46 [small]; $P = 0.038$). Small to moderate significant increases in UA concentration were found in the 10-over trial at both pre to post ($\Delta 13 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI 2 to 24; ES = 0.53 [small]; $P = 0.05$) and pre to 24 h post ($\Delta 20 \mu\text{mol}\cdot\text{L}^{-1}$; 90% CI 4 to 36; ES = 0.81 [moderate]; $P = 0.044$), respectively. There were no significant differences ($P \geq 0.05$) between UA concentrations and the time-course of recovery following either 4- or RAND-overs following the CA-AIS fast bowling trials.

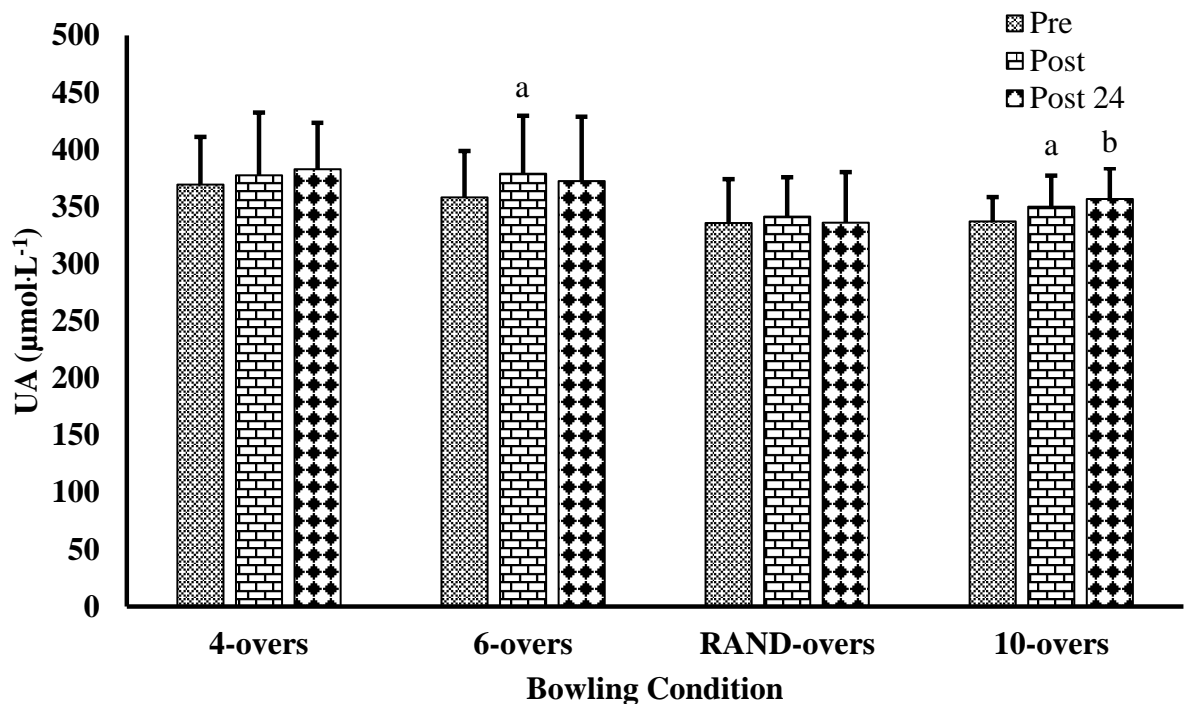


Figure 7.3. Plasma uric acid (UA) concentration ($\mu\text{mol}\cdot\text{L}^{-1}$) as a result of simulated fast bowling; a: significant difference from pre to post ($P \leq 0.05$); b: significant difference from pre to 24 h post ($P \leq 0.05$). Data presented as mean \pm SD.

Plasma urea concentrations

A trivial, significant increase in plasma urea concentration was found pre to post (Δ 0.15 mmol·L⁻¹; 90% CI 0.07 to 0.2; ES = 0.14 [trivial]; $P = 0.001$) fast bowling simulation. Trivial, non-significant increases were found in plasma urea concentrations at both pre to 24 h post (Δ 0.06 mmol·L⁻¹; 90% CI -0.3 to 0.4; ES = 0.06 [trivial]; $P = 1.00$) and post to 24 h post simulation (Δ 0.09 mmol·L⁻¹; 90% CI -0.3 to 0.4; ES = 0.09 [trivial]; $P = 1.00$), respectively. Figure 7.4. illustrates the individual urea responses following each CA-AIS fast bowling trial. Specifically, no significant differences ($P \geq 0.05$) between urea concentrations and the time-course of recovery following any of the CA-AIS fast bowling trials were found.

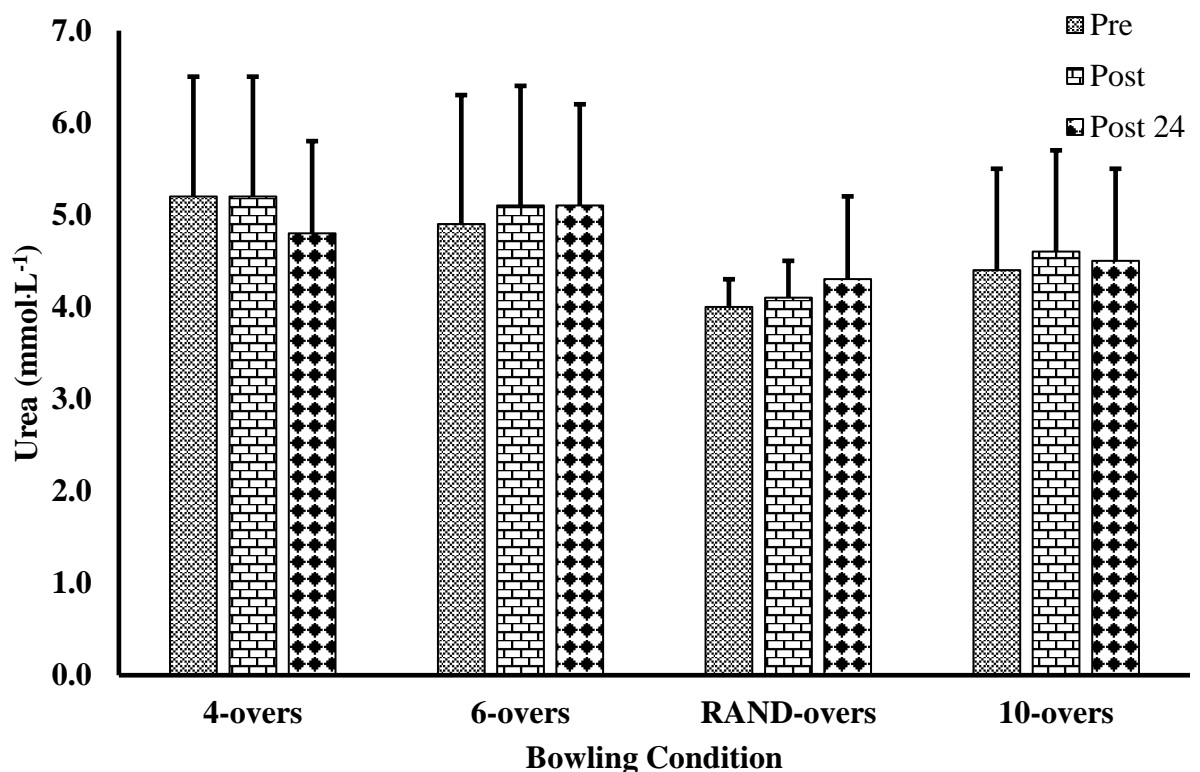


Figure 7.4. Plasma urea concentration (mmol·L⁻¹) as a result of simulated fast bowling. Data presented as mean \pm SD.

Salivary cortisol (sCort) concentrations

There were large to moderate significant reductions in sCort pre to post (Δ 9.6 ng·mL⁻¹; 90% CI 6.2 to 12.8; ES = 1.38 [large]; $P \leq 0.01$) and pre to 24 h post fast bowling simulation (Δ 6.2 ng·mL⁻¹; 90% CI 2.3 to 10.2; ES = 0.64 [moderate]; $P = 0.004$), respectively. There was a trivial, significant increase in sCort post to 24 h post simulation (Δ -3.3 ng·mL⁻¹; 90% CI -0.3 to -6.3; ES = -0.55 [trivial]; $P = 0.05$). Figure 7.5 illustrates the individual sCort responses following each CA-AIS fast bowling trial. Specifically, as a result of bowling 4-overs, a large significant decrease in sCort concentration was found pre to post simulation (Δ 13 ng·mL⁻¹; 90% CI 3 to 22; ES = 1.23 [large]; $P = 0.025$). As a consequence of bowling 6-overs, a moderate significant reduction in sCort was found pre to 24 h post (Δ 3 ng·mL⁻¹; 90% CI 1 to 6; ES = 0.88 [moderate]; $P = 0.038$), with a large significant increase in sCort found post to 24 h post simulation (Δ 4 ng·mL⁻¹; 90% CI 1 to 8; ES = 1.33 [large]; $P = 0.036$). As a result of bowling RAND-overs, a large significant decrease in sCort concentration was found pre to post simulation (Δ 5 ng·mL⁻¹; 90% CI 2 to 8; ES = 1.37 [large]; $P = 0.005$), with a large significant increase observed post to 24 h post simulation (Δ 4 ng·mL⁻¹; 90% CI 2 to 7; ES = 1.33 [large]; $P = 0.007$). As a consequence of bowling 10-overs, very large significant reductions in sCort were found pre to post (Δ 19 ng·mL⁻¹; 90% CI 10 to 30; ES = 2.42 [very large]; $P = 0.003$) and pre to 24 h post simulation (Δ 19 ng·mL⁻¹; 90% CI 8 to 29; ES = 2.27 [very large]; $P = 0.003$), respectively.

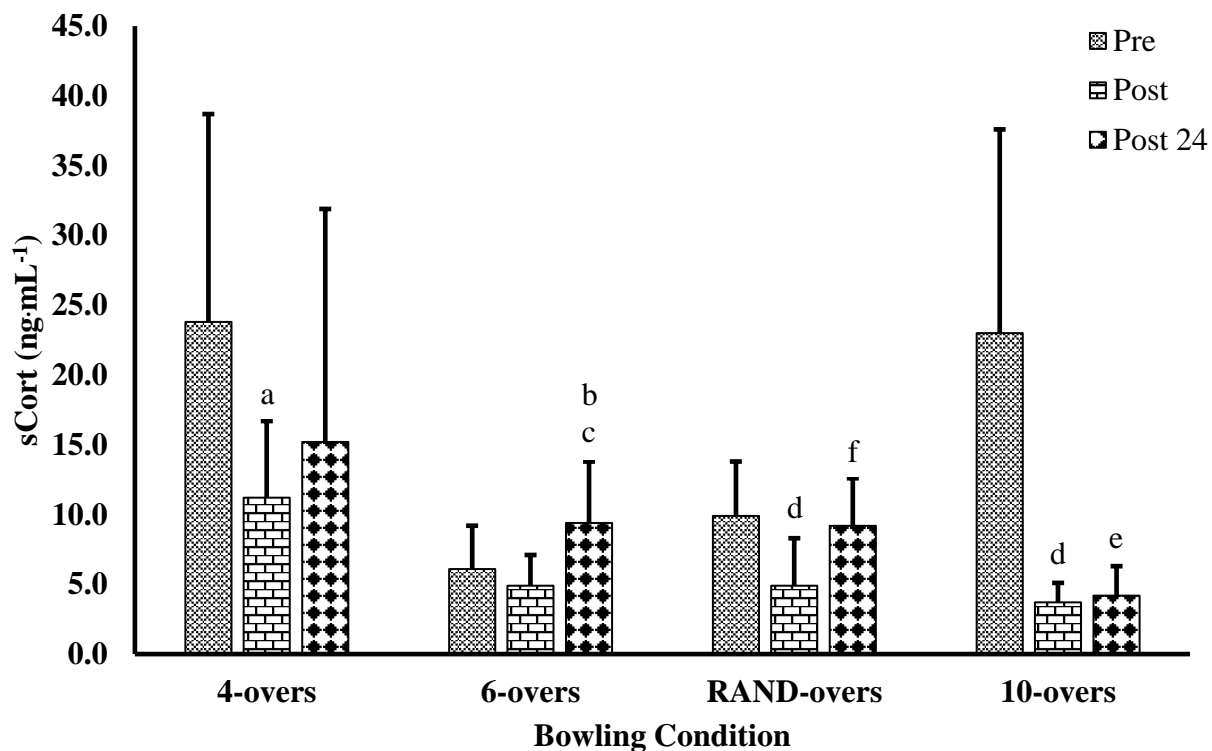


Figure 7.5. Salivary cortisol (sCort) concentration ($\text{ng}\cdot\text{mL}^{-1}$) as a result of simulated fast bowling; a: significant difference from pre to post ($P \leq 0.05$); b: significant difference from pre to 24 h post ($P \leq 0.05$); c: significant difference from post to 24 h post ($P \leq 0.05$); d: significant difference from pre to post ($P \leq 0.01$); e: significant difference from pre to 24 h post ($P \leq 0.01$); f: significant difference from post to 24 h post ($P \leq 0.01$). Data presented as mean \pm SD.

Perceived Well-Being

Perceived well-being at pre and 24 h post simulation are shown in Table 7.2. There was a moderate significant main effect of time in perceived well-being from pre to 24 h post simulation (Δ 2.2 AU; 90% CI 1.6 to 2.8; ES = 1.01 [moderate]; $P < 0.01$). When analysed dependent of simulated fast bowling load, a non-significant reduction was found in the perceived well-being pre to 24 h post simulation after bowling 4-overs (Δ 1.3 AU; 90% CI 0.1 to 2.5; ES = 0.61 [moderate]; $P = 0.08$). There were

moderate to large significant reductions in perceived well-being pre to 24 h post simulation at 6-overs (Δ 2.7 AU; 90% CI 1.5 to 4.0; ES = 0.95 [moderate]; $P = 0.003$), RAND-overs (Δ 2.3 AU; 90% CI 0.1 to 3.7; ES = 1.21 [large]; $P = 0.019$) and 10-overs (Δ 2.5 AU; 90% CI 1.3 to 3.6; ES = 1.39 [large]; $P = 0.003$), respectively.

Rating of Perceived Exertion

The RPE and sRPE for each simulated spell of fast bowling are displayed in Table 7.2. There was a significant main effect between groups for number of overs bowled during the CA-AIS fast bowling simulation ($P \leq 0.01$). Further between-group analyses identified a non-significant difference in sRPE between 4- and 6-overs (Δ 101.7 AU; 90% CI 0.6 to 202.9; ES = 2.56 [very large]; $P = 0.10$). Very large significant differences were found in sRPE between 4- and RAND-overs (Δ 250.1 AU; 90% CI 148.9 to 351.3; ES = 3.68 [very large]; $P \leq 0.01$) and 10-overs (Δ 396.0 AU; 90% CI 294.4 to 497.2; ES = 4.69 [very large]; $P \leq 0.01$), respectively. Moreover, large and very large significant differences were found in sRPE between 6- and RAND-overs (Δ 148.4 AU; 90% CI 47.2 to 294.5; ES = 1.81 [large]; $P = 0.004$) and 10-overs (Δ 294.3 AU; 90% CI 193.1 to 395.4; ES = 2.99 [very large]; $P \leq 0.01$). A moderate significant difference was found in sRPE between RAND- and 10-overs (Δ 145.9 AU; 90% CI 44.8 to 247.1; ES = 1.15 [moderate]; $P = 0.005$), respectively.

Relationship between performance and subjective CA-AIS simulation data and CMJ flight-time

Correlations between Δ CMJ [pre_post], Δ CMJ 24 [pre_24-h post] and performance and subjective CA-AIS simulation data are reported below (Figure 7.6.). There was a moderate relationship between Δ CMJ 24 and perceptual well-being 24 h post

simulation ($r = 0.38$; 90% CI 0.14 to 0.58; $P = 0.011$). A moderate inverse relationship was observed between Δ CMJ 24 and RPE ($r = -0.30$; 90% CI -0.51 to -0.05; $P = 0.049$). The magnitude of correlation between all the other variables was trivial or small and non-significant ($P \geq 0.05$). This data is further categorised to account for each individual simulated fast bowling trial.

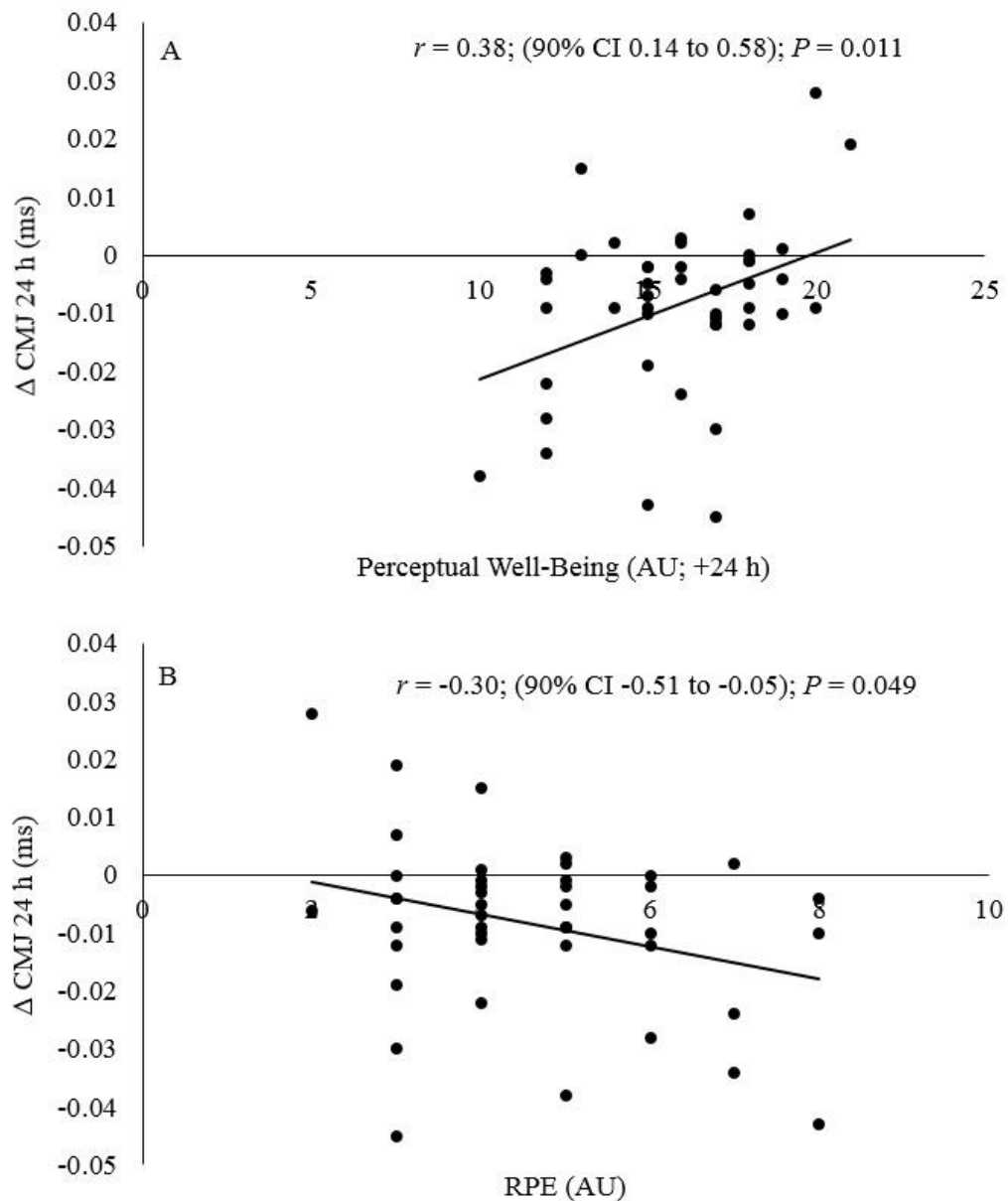


Figure 7.6. – Relationships between (A) Δ CMJ 24 h flight-time (ms) and perceptual

well-being (AU; + 24 h), and (B) Δ CMJ 24 h flight-time (ms) and RPE (AU). CMJ = Countermovement jump; RPE = Rating of Perceived Exertion.

4-overs; a moderate relationship was observed between Δ CMJ 24 and post simulation wellness (+ 24-h; $r = 0.62$; 90% CI 0.14 to 0.68; $P = 0.043$) (Figure 7.7.).

10-overs; moderate to large inverse relationships were found in RPE at both Δ CMJ ($r = -0.69$; 90% CI -0.89 to -0.26; $P = 0.018$) and Δ CMJ 24 ($r = -0.72$; 90% CI -0.90 to -0.32; $P = 0.013$), respectively. Similarly, a moderate relationship was found between sRPE and Δ CMJ ($r = -0.64$; 90% CI -0.87 to -0.17; $P = 0.033$) (Figure 7.7.).

The remainder of the relationships was small to moderate (range; -0.62 to 0.55) and non-significant ($P > 0.05$).

Relationships between training load, subjective CA-AIS simulation data and biochemical and endocrine measures

Correlations between Δ CK [pre_post], Δ CK 24 [pre_24 h post], training load and subjective CA-AIS simulation data are reported in Figures 7.7 – 7.10., respectively.

Correlations between Δ UA [pre_post], Δ UA 24 [pre_24 h post], Δ Urea [pre_post], Δ Urea 24 [pre_24 h post] and Δ sCort [pre_post], Δ sCort 24 [pre_24 h post], training load and subjective CA-AIS simulation data are reported below. There was a moderate significant relationship found between simulation duration and Δ CK 24 ($r = 0.49$; 90% CI 0.26 to 0.67; $P = 0.001$). A moderate relationship was observed between Δ CK 24 and number of deliveries bowled ($r = 0.48$; 90% CI 0.25 to 0.66; $P = 0.002$). Moderate relationships were found between run-up speed and Δ Urea 24 ($r = 0.36$; 90% CI 0.11 to 0.57; $P = 0.022$) with an inverse relationship found for Δ UA ($r = -0.31$; 90% CI -0.53 to -0.06; $P = 0.046$), respectively. A moderate relationship between

estimated TD was found at both Δ CK ($r = 0.32$; 90% CI 0.07 to 0.53; $P = 0.038$) and Δ CK 24 ($r = 0.48$; 90% CI 0.25 to 0.66; $P = 0.002$), respectively. Moderate inverse relationships were found between estimated relative TD and UA at both time points; Δ UA ($r = -0.36$; 90% CI -0.57 to -0.11; $P = 0.018$) and Δ UA 24 ($r = -0.49$; 90% CI -0.67 to -0.26; $P = 0.004$). A moderate significant relationship was found between PL and Δ CK 24 ($r = 0.41$; 90% CI 0.16 to 0.61; $P = 0.009$). Similarly, a moderate relationship was found between HREI and Δ CK 24 ($r = 0.45$; 90% CI 0.21 to 0.64; $P = 0.003$). A moderate significant relationship was found between pre-simulation perceived wellness and Δ CK ($r = 0.32$; 90% CI 0.07 to 0.53; $P = 0.04$). A moderate inverse relationship was observed between post-simulation perceived wellness and Δ sCort ($r = -0.41$; 90% CI -0.60 to -0.18; $P = 0.005$). A moderate significant relationship was found between RPE and Δ CK 24 ($r = 0.47$; 90% CI 0.24 to 0.65; $P = 0.002$). Finally, moderate relationships were observed between sRPE and Δ CK ($r = 0.33$; 90% CI 0.08 to 0.54; $P = 0.032$) and Δ CK 24 ($r = 0.48$; 90% CI 0.25 to 0.66; $P = 0.002$), respectively. The magnitude of the correlation between all the other variables was trivial to small ($P \geq 0.05$). This data is further categorised to account for each four simulated fast bowling training load.

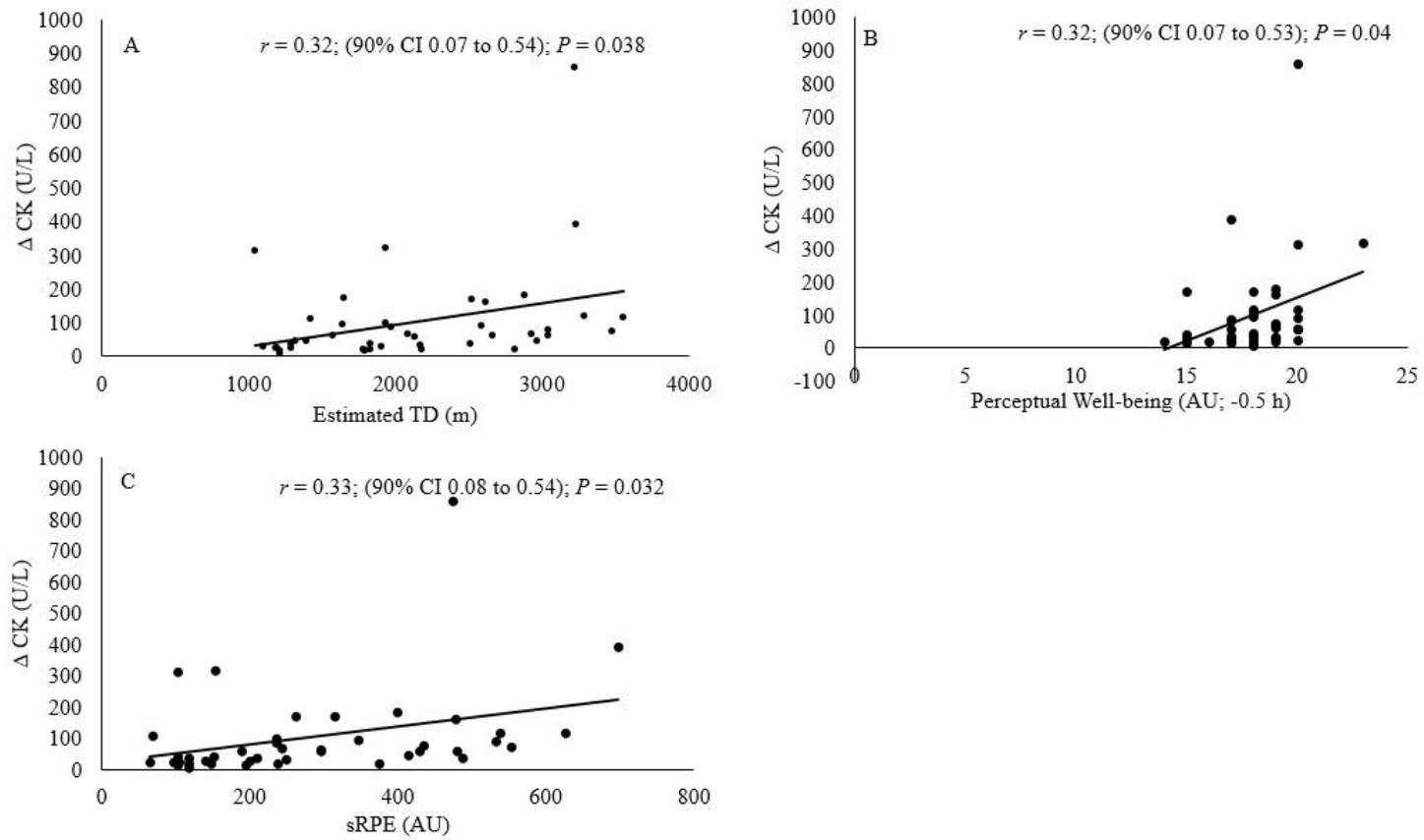


Figure 7.7. – Relationships between (A) Δ CK 0.5 h (U/L) and estimated TD (m), AU; + 24 h), (B) Δ CK 0.5 h (U/L) and perceptual well-being, and (C) Δ CK 0.5 h (U/L) and sRPE (AU). CK = Creatine kinase; TD = Total distance; sRPE = session Rating of Perceived Exertion.

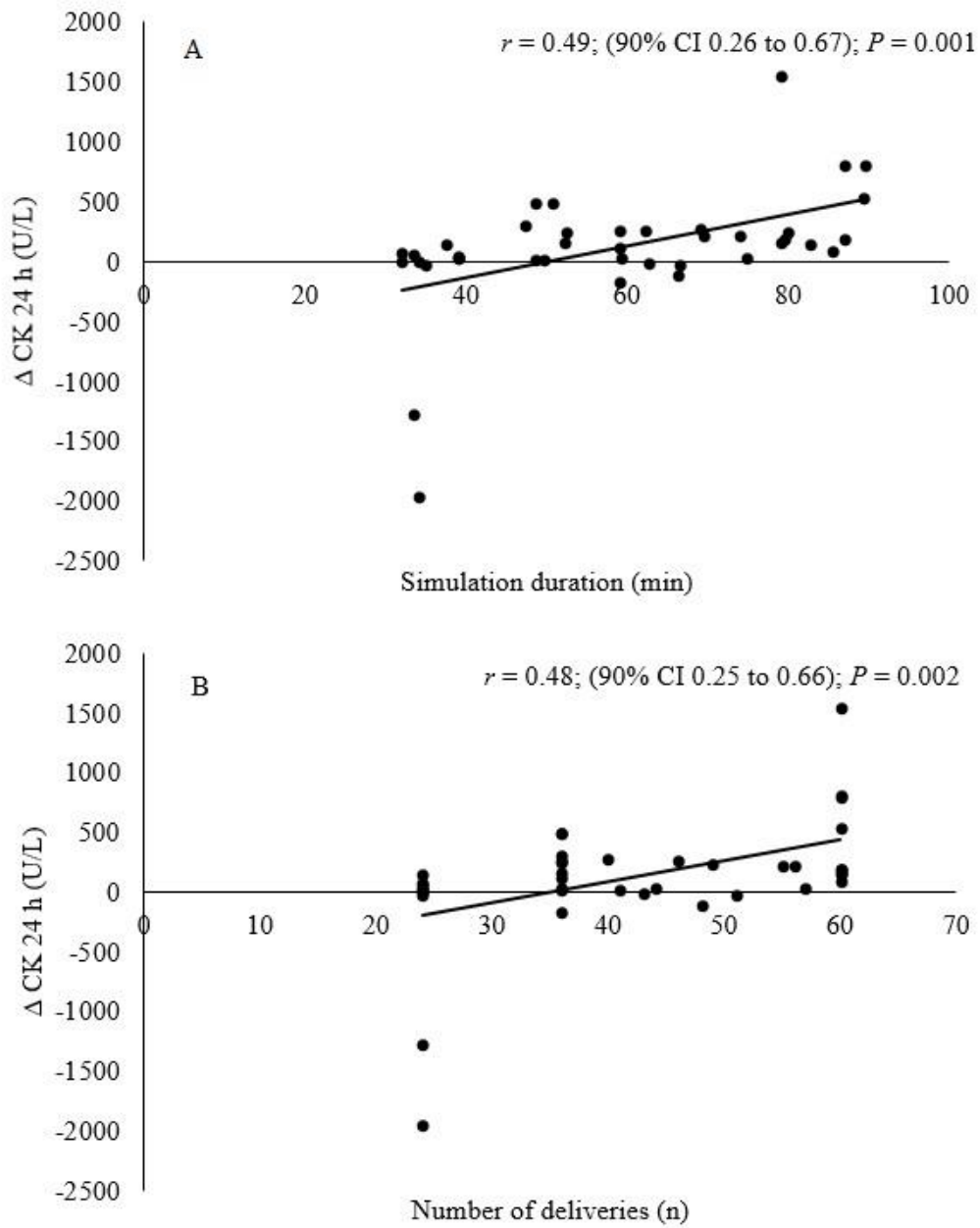


Figure 7.8. – Relationships between (A) Δ CK 24 h (U/L) and simulation duration (min), and (B) Δ CK 24 h (U/L) and number of deliveries bowled (n). CK = Creatine kinase.

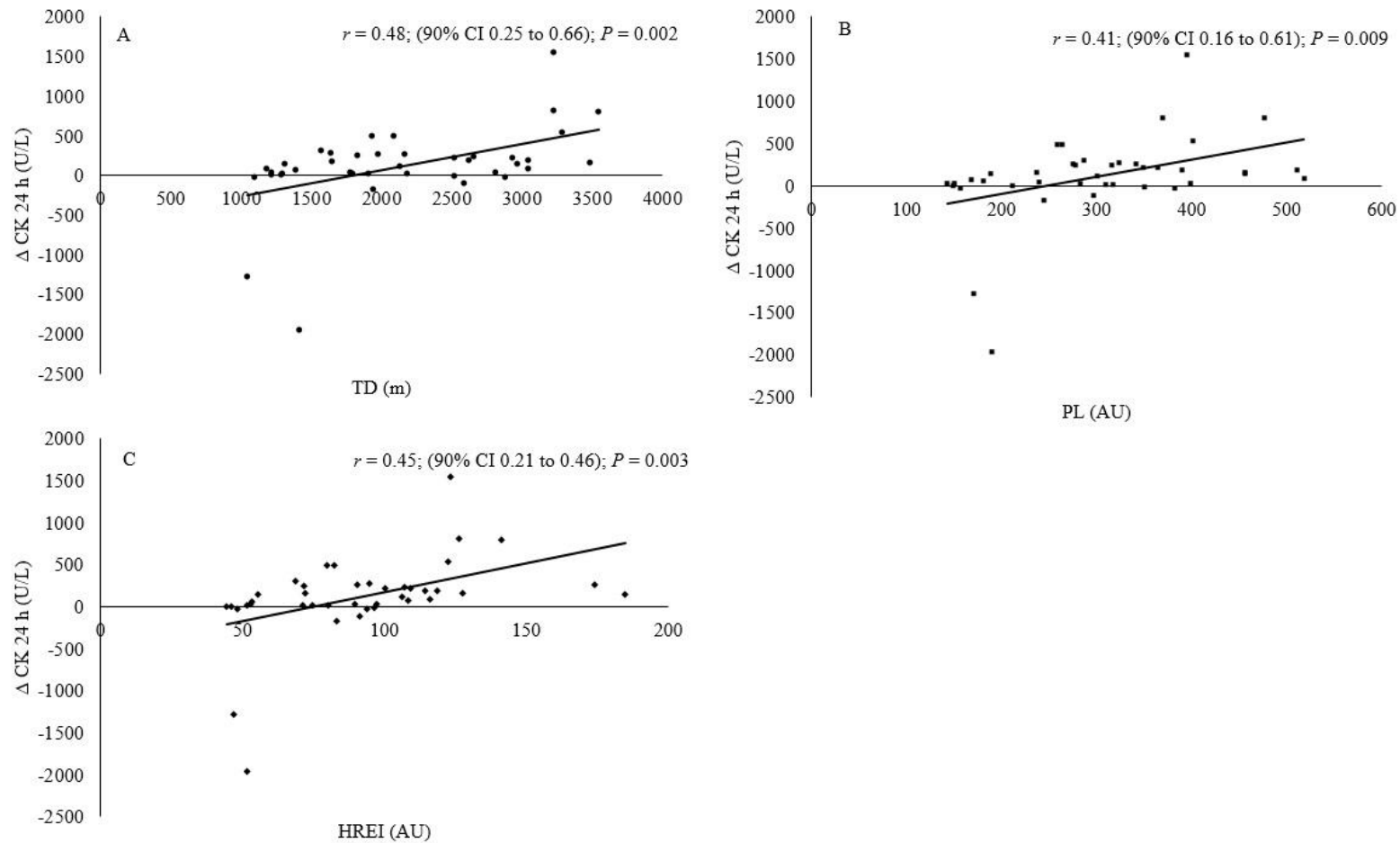


Figure 7.9. – Relationships between (A) Δ CK 24 h (U/L) and estimated TD (m), (B) Δ CK 24 h (U/L) and PL (AU), and Δ CK 24 h (U/L) and HREI (AU). CK = Creatine kinase; TD = Total distance; PL = PlayerLoad™; HREI = Heart Rate Exertion Index.

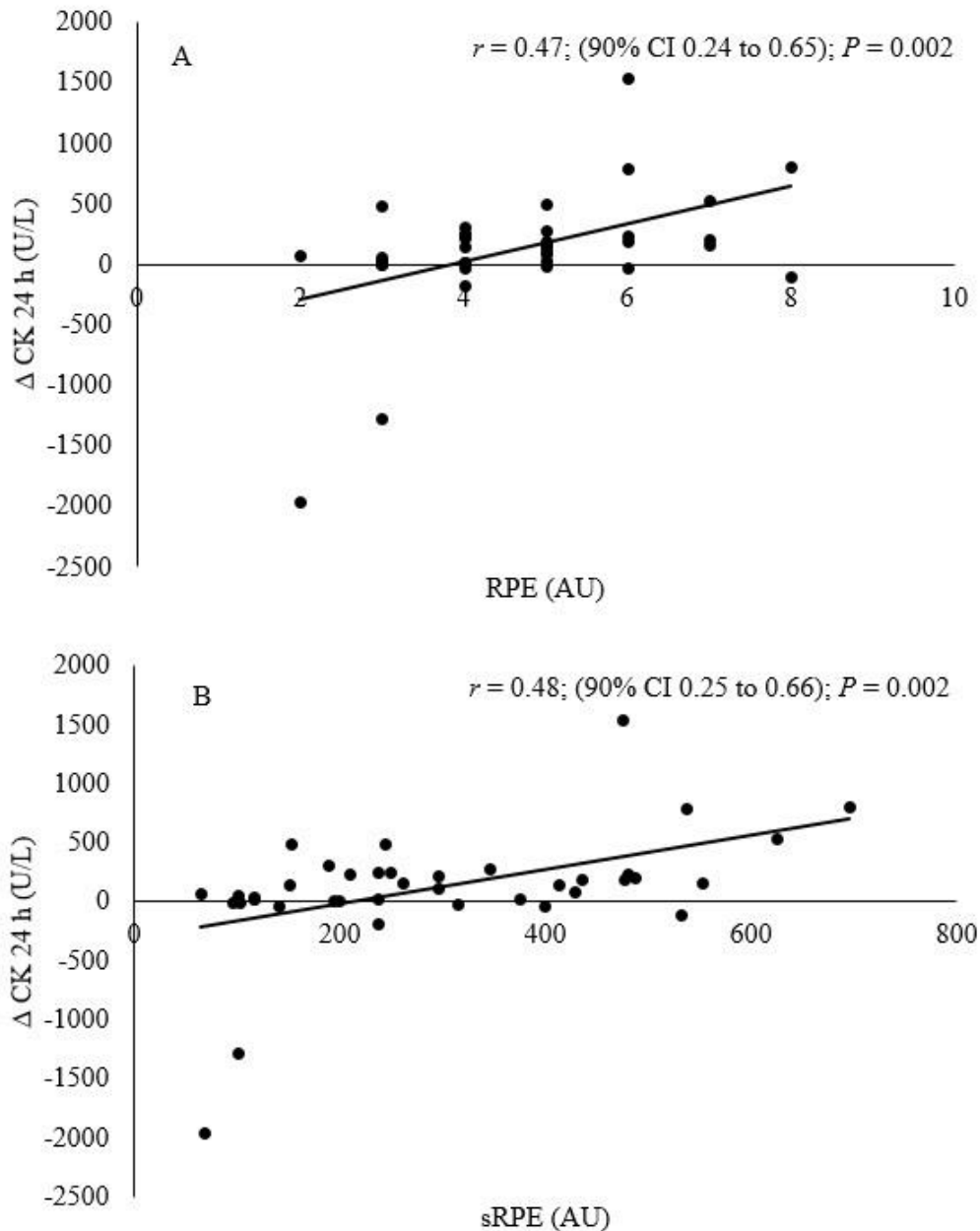


Figure 7.10. – Relationships between (A) Δ CK 24 h (U/L) and RPE (AU), and (B) Δ CK 24 h (U/L) and sRPE (AU). CK = Creatine kinase; RPE = Rating of Perceived Exertion; sRPE = session Rating of Perceived Exertion.

4-overs; a moderate inverse relationship was found between Δ Urea and PL ($r = -0.65$; 90% CI -0.88 to 0.19; $P = 0.032$). Moderate to large relationships were found in PL at both Δ sCort ($r = 0.70$; 90% CI 0.28 to 0.90; $P = 0.018$) and Δ sCort 24 ($r = 0.79$; 90% CI 0.45 to 0.93; $P = 0.004$), respectively. A large relationship was found

between relative PL and Δ sCort 24 ($r = 0.78$; 90% CI 0.43 to 0.93; $P = 0.005$). A moderate inverse relationship was present between post-simulation wellness (+ 24 h) and Δ sCort ($r = -0.67$; 90% CI -0.88 to -0.23; $P = 0.025$).

6-overs; a large relationship was found between duration of simulation and Δ sCort 24 ($r = 0.78$; 90% CI 0.43 to 0.93; $P = 0.005$). A moderate inverse relationship was observed between estimated TD and Δ sCort ($r = -0.65$; 90% CI -0.88 to -0.19; $P = 0.032$). Similarly, a moderate relationship existed between relative PL and Δ sCort 24 ($r = -0.70$; 90% CI -0.90 to -0.28; $P = 0.016$).

RAND-overs; Pre_post Δ CK demonstrated a moderate relationship in total run-up speed ($r = 0.61$; 90% CI 0.13 to 0.86; $P = 0.046$), with a large relationship present in the run-up speed during the final 5 m ($r = 0.73$; 90% CI 0.33 to 0.91; $P = 0.011$). There were moderate to large inverse relationships between estimated relative TD and Δ CK 24 ($r = -0.67$; 90% CI -0.88 to -0.23; $P = 0.026$), Δ UA ($r = -0.63$; 90% CI -0.87 to -0.16; $P = 0.036$), Δ UA 24 ($r = -0.83$; 90% CI -0.94 to -0.54; $P = 0.002$) and Δ Urea 24 ($r = -0.70$; 90% CI -0.90 to -0.28; $P = 0.018$), respectively. A moderate relationship was found between pre-simulation wellness (-0.5 h) and Δ CK 24 ($r = 0.63$; 90% CI 0.16 to 0.87; $P = 0.036$). An inverse moderate relationship was found between Δ Urea and post-simulation wellness (+ 24 h; $r = -0.65$; 90% CI -0.88 to -0.19; $P = 0.031$).

10-overs; large relationships were found between both between duration of simulation and Δ UA 24 ($r = 0.85$; 90% CI 0.53 to 0.96; $P = 0.003$) and total run-up speed and Δ Urea 24 ($r = 0.72$; 90% CI 0.23 to 0.92; $P = 0.029$), respectively. The remainder of the relationships was small to moderate (range; -0.59 to 0.62) and non-significant ($P > 0.05$).

7.4. Discussion

The purpose of this experimental chapter was to explore short-term (+24 h post) NMF and the biochemical and endocrine responses to simulated indoor fast bowling. Results show that CMJ performance was reduced post simulation, remaining significantly suppressed at 24 h post simulation. Results also show that most of the biochemical and endocrine concentrations were significantly effected as a result of simulated fast bowling. Furthermore, results show that psychological variables can detect changes in fatigue following spells of fast bowling. Collectively, these findings support our initial hypothesis, which states that longer bowling spells will result in substantial increases in NMF, EIMD and endocrine measures post-simulation. These findings support the application of analysis of neuromuscular, biochemical, endocrine and psychometric assessments in monitoring the acute fatigue responses to simulated fast bowling in cricket. However, caution is required, if such variables are to be used to inform training performed after 24 h.

There were significant reductions in CMJ flight-time (+ 0.5 h) immediately following simulated fast bowling. These significant reductions were typically magnified as a result of increased fast bowling workloads (see Figure 7.1.). Similarly, significant reductions were found in CMJ flight-time at 24 h post simulation. However, unlike immediately post, the magnitude of these reductions was attenuated when factoring in fast bowling workloads. Interestingly, our findings tend to disagree with previous research (Duffield et al., 2009; McNamara et al., 2013; Minett et al., 2012a, 2012b), who have suggested that a spell(s) of fast bowling fails to elicit a significant reduction in CMJ flight-time. However, of these simulated fast bowling studies (Duffield et al., 2009; Minett et al., 2012a, 2012b), the assessment of NMF was only a surrogate measure, with bowlers typically bowling 6-overs. Therefore, it

may be postulated that fast bowlers are suitably conditioned to tolerate bowling loads of this nature (6-overs). However, this conflicts with our findings, where we have shown that, following a simulated 6-over spell, a moderate significant reduction in CMJ flight time pre to post was found (Δ 26 ms; 90% CI 17 to 34; ES = 0.63 [moderate]; $P < 0.01$). Moreover, the reduction in CMJ flight-time in this study has been further supported by other team sport simulations, showing immediate reductions in CMJ performance (Gathercole et al., 2015b; Thorlund et al., 2008). Despite reductions in CMJ flight-time found at 24 h post, these tended to be small and consequently conflict with the existing literature, showing that CMJ performance is significantly attenuated at 24 h and can remain compromised for up to 72 h (Andersson et al., 2008; Cormack et al., 2013; Cormack, Newton, McGuigan, & Cormie, 2008; Duffield et al., 2012; McLean et al., 2010; Ronglan et al., 2006; Wehbe et al., 2015). However, most of this data is taken from contact sport competition, which is typically considered to present far greater physical demands on players.

The profile and changes in biochemical and endocrine concentrations are widely accepted as markers of physiological and psychological stress and muscle damage in team sports (Buchheit et al., 2013; Cormack, Newton, & McGuigan, 2008; Hunkin et al., 2014; M. J. Johnston et al., 2016; R. D. Johnston et al., 2014; A. Scott et al., 2016; Slattery et al., 2012). The results from biochemical analysis tended to mimic that of NMF, whereby plasma CK, UA and urea concentrations significantly increased and peaked immediately following (+ 0.5 h) simulated fast bowling. Specifically, CK concentrations were significantly increased as a result of the increased fast bowling workloads (see Figure 7.2.). Although, 6-, RAND- and 10-overs all displayed significant increases in plasma CK immediately post simulation, the 10-over spell was the only fast bowling condition to show significantly elevated

CK concentrations at 24 h post. The results from this study tend to agree with those earlier studies (Lombard et al., 2012; Minett et al., 2012a, 2012b), who have also investigated the impact of simulated fast bowling on skeletal muscle-damage or blood CK concentration. Firstly, this study confirms that simulated fast bowling is sufficient to significantly elevate CK immediately after and 24 h following an extended spell (\geq 6-overs) of simulated fast bowling. However, the increase in CK becomes somewhat attenuated dependent on the duration of bowling spell. Furthermore, this study has been able to identify that a “dose-response” relationship could exist between fast bowling training load and EIMD, which is reflected in a number of correlations between Δ CK 24 h and both internal (HREI $r = 0.45$; $P = 0.003$) and external training load (estimated TD $r = 0.48$; $P = 0.002$; PL $r = 0.41$; $P = 0.009$) measures. Despite disagreeing with the limited cricket literature, these results support data from other team sports, which tend to show that CK concentrations are significantly elevated at 24 h post-match and are influenced by global measures of external training load (TD) (M. J. Johnston et al., 2016; R. D. Johnston et al., 2014; McLellan et al., 2010; C. P. McLellan et al., 2011a). However, it is important to acknowledge that most of these studies are taken after competition and not a simulated aspect of match-play.

Uric acid and urea concentrations both increased significantly immediately following the fast bowling simulation, with UA the only biochemical parameter to remain significantly elevated 24 h post simulation. Firstly, the increase in UA and urea immediately post simulation support earlier team sport studies (Andersson et al., 2008; Bangsbo, 1994), that both found acute increases following a 90-min soccer match. However, the continued significantly elevated UA concentrations 24 h post simulation partly conflict with earlier literature, which tends to show that both UA and urea tend to return to near basal levels within 21 h (Andersson et al., 2008; Bangsbo, 1994).

Specifically, like plasma CK, UA also tended to show that, as bowling workload increased, so did the magnitude of the effect between the pre to post measures (see Figure 7.3.). However, these significant differences were only found in UA, with no specific differences found as a result of increased fast bowling training load in urea.

Changes in sCort typically displayed the largest significant differences between pre-simulation values and at both time points following simulated fast bowling (+ 0.5- and +24-h post). To date, McNamara and colleagues (2013) are the only researchers to outline endocrine responses of cricketers to competition and training. Unfortunately, the authors present this data as a comparison between fast bowlers and non-fast bowlers, making comparisons to this data difficult. However, it is important to acknowledge that, during both training and competition phases, fast bowlers tended to present significantly greater sCort concentrations than non-fast bowlers, which was attributed to the increased training loads of fast bowlers. Furthermore, when accounting for individual fast bowling workloads, the results comprehensively indicate the significant reductions in sCort concentrations as a result of the increased fast bowling loads (see Figure 7.5.). Specifically, once fast bowlers tend to bowl a spell of 6-overs or longer, there are large significant changes in sCort, remaining present for 24 h post simulation. These significantly reduced sCort concentrations up to 24 h post bowling simulation agree with earlier research reporting decreased cortisol following team sport competition (Elloumi, Maso, Michaux, Robert, & Lac, 2003).

Similar to the aforementioned neuromuscular, biochemical and endocrine measures, there was a significant effect of fast bowling workload on perceived well-being (+24 h). In addition to the overall reduction in perceived well-being when accounting for individual bowling workloads, there was a general trend for an

increased fast bowling load reflecting a decreased well-being score (see Figure 7.6.). Previous research has also provided data pertaining to changes in an athlete's perceived well-being, showing that, as a result of increased training loads or following competition, perceived well-being was significantly effected (Coutts, Slattery, et al., 2007; McLean et al., 2010; Thorpe et al., 2015).

The data presented suggest that perceptual well-being appears to relate to changes in neuromuscular function (assessed via a CMJ). Specifically, a significant correlation was observed between perceptual well-being ($r = 0.38$) and changes in CMJ performance 24 h post simulation. However, an unexpected outcome from this study is the negative association between RPE ($r = -0.30$) and the change in CMJ performance 24 h post simulation. Moreover, when accounting for fast bowling workloads, a significant negative relationship was found between RPE ($r = -0.69$) and sRPE ($r = -0.64$) and changes in CMJ performance immediately following simulated fast bowling. Subsequent analysis 24 h post simulation also showed a significant inverse relationship between RPE ($r = -0.72$) and CMJ flight-time after bowling 10-overs. This is an extremely surprising finding, given that team sport research tends to show a positive association between changes in CMJ performance and RPE (Balsalobre-Fernández, Tejero-González, & del Campo-Vecino, 2014). A possible explanation for this phenomenon is referred to as regression to the mean. This occurs when participants present extreme values on the pre-test, with less extreme values collected on the post-test (Nevill, Holder, Atkinson, & Copas, 2004). Subsequent analysis was performed to explore this by correlating CMJ flight-time Δ CMJ (pre value – post value), Δ CMJ 24 (pre value – 24-h post value) and the sum of both scores (post value + pre value). The results from this analysis identified a near inverse relationship for Δ CMJ ($r = 0.07$) and a negative relationship for Δ CMJ 24 ($r = -0.06$),

respectively. These findings thereby provide some further evidence for regression toward the mean (Nevill et al., 2004).

Finally, we explored relationships between the same performance and subjective CA-AIS simulation data (as above) and biochemical and endocrine measures. It was observed that changes in CK appear to be the primary biochemical measure that strongly relates to subjective, internal and external training load measures. Specifically, a significant correlation was found immediately post simulation between CK and estimated TD ($r = 0.32$ [moderate]). These findings have been supported from earlier studies from rugby league (Oxendale et al., 2016) and Australia Rules Football (Young et al., 2012), both showing strong relationships ($r \geq 0.5$) with CK concentrations and TD. Furthermore, significant relationships were found between CK concentrations 24 h post simulation and simulation duration ($r = 0.49$), number of deliveries bowled ($r = 0.48$), PL ($r = 0.41$), HREI ($r = 0.45$), RPE ($r = 0.47$), and sRPE ($r = 0.48$), respectively (see Table 7.5.). Again, although not cricket-specific, these findings are in agreement with data from other team sports, showing associations with match duration ($r \geq 0.9$) and acceleration data ($r \geq 0.4$) (Hunkin et al., 2014; Oxendale et al., 2016; Young et al., 2012). The use of MEMS data to predict EIMD could be of use to coaches and practitioners in prescribing recovery strategies. Specifically, a more individualised strategy could be derived based on the moderate relationships observed between CK and TD, PL and HREI, respectively. For example, as the PL variable incorporates combinations of both running and impact events (i.e. bowling action), it is feasible, that, once players achieve a higher PL than normal, an adjustment of subsequent training loads may be required to accelerate recovery. Conversely, when this technology is unavailable, it could be proposed that similar training load prescription could be employed based on the moderate relationships

observed in CK and descriptive data (i.e. deliveries bowled). Coaches and practitioners should look to exploit information pertaining to EIMD and training load, thus potentially achieving a competitive advantage.

Collectively these findings support the monitoring of neuromuscular function, psycho-biological markers (RPE derivatives) and CK concentrations up to 24 h following simulated fast bowling to indicate EIMD. These symptoms may also compromise the quality of a player's subsequent performance in training or competition, which may be amplified further during periods of condensed scheduling (Oxendale et al., 2016), which are common in professional cricket.

8. General Discussion, Conclusions, Limitations, Future Research

Recommendations and Practical Applications

This final chapter is intended to summarise the primary aims of this thesis and to synthesise the findings from both the descriptive and experimental research chapters. Furthermore, this chapter will identify the limitations within the thesis and provide future research recommendations and practical applications. This thesis is the result of one descriptive (see Chapter 4) and three experimental studies (see Chapters 5 – 7). The descriptive and first two experimental studies used professional fast bowlers from a single England and Wales Cricket Board (ECB) County Cricket Club. The final experimental chapter used a group of part-time senior club-level fast bowlers. The aims of this thesis were:

1. Describe the typical fast bowling workload characteristics during a professional county cricket season, differentiating between opening and support bowlers.
2. Analyse the between- and within-match variability of external training load measures of professional fast bowlers during professional T20 cricket.
3. Monitor the short-term NMF patterns of fast bowlers following OD limited overs cricket, whilst highlighting between-match variability.
4. Assess the short-term NMF, biochemical and endocrine responses to a controlled fast bowling simulation.
5. Examine the validity and practical application of MEMS technology to monitor training load of fast bowlers.

8.1. General Discussion

The global aim of this thesis was to examine the utility of GPS-accelerometry data derived from a MEMS device to quantify training load in cricket fast bowling, with special reference to assessing fatigue and recovery. Therefore, it is of paramount importance to identify a valid, reliable and cricket-specific measure of fatigue and training load for coaches and cricket practitioners (McNamara et al., 2016). Longer term, it is hoped that this thesis will aid in the further justification for the collection of descriptive fast bowling workload data coupled with MEMS training load data to facilitate an evidence based approach to training load prescription. Specifically, it is hoped that by sub-dividing fast bowlers (O-B vs S-B) and highlighting periods of differing fixtures (MD vs OD vs T20), practitioners may be able to adopt a more individualised approach to training load prescription (workload thresholds) and recovery. In turn, this may aid in an increased awareness of the competition-specific fatigue and time-course recovery associated with differing fast bowling volumes, thus developing the training efficiency of cricket fast bowlers. Collectively, it is hoped that this will ultimately prevent injury.

During the past decade, TMA systems such as video recording and computer digitalisation have been used to quantify external training loads (Boyd et al., 2011; Dellaserra et al., 2014). However, despite these systems, fast bowling loads can still be obtained with minimal equipment in the form of notational analysis providing descriptive data from cricket scorecards and fixture lists. In light of this, this thesis firstly sought to provide a descriptive analysis of fast bowling competition loads obtained from cricket scorecards. Furthermore, it is important to acknowledge that bowlers within the same team can experience substantially different competition loads, depending on length of bowling spell, number of deliveries bowled and their

role within a match (Olivier et al., 2016; Stronach et al., 2014). Therefore, by differentiating by bowler classification (opening vs support bowler), this descriptive chapter was able to provide a novel approach to monitoring fast bowling competition loads, potentially eliminating some of the inherent associated bowling workload variability. This is an important consideration, as it has previously been suggested (Petersen et al., 2008), that there is an increased reliance on opening bowlers, as they are typically perceived as being the most capable of taking wickets.

Several longitudinal investigations have reported on fast bowling workloads and the associated injury rates in both junior and senior professional cricketers (Dennis et al., 2004; Dennis et al., 2003; Dennis et al., 2005; Hulin et al., 2014; Orchard et al., 2009). A high bowling load, as well as abnormally low bowling loads, have both been linked to an increased injury risk (Dennis et al., 2003; Hulin et al., 2014; Olivier et al., 2016; Orchard et al., 2015; Orchard et al., 2009; Orchard et al., 2016). However, despite this increasing body of literature, there is still a distinct lack of descriptive data detailing typical competition fast bowling loads. Furthermore, these studies have typically sourced data from Australian cricketers, who do not tend to experience the “block” approach to fixture scheduling, where players experience condensed periods of one game format, unlike ECB county cricketers.

The results from Chapter 4 clearly show that there were very large differences between opening and support fast bowlers in terms of competition loads (overs and deliveries bowled). However, further analysis only identified that this was apparent during the County Championship competition. Moreover, the results from this chapter also highlighted that there was a significant difference between cumulative fast bowling loads (spanning the season). Further analysis highlighted large differences in

fast bowling loads during the first and last quarters of the season, respectively. A possible explanation for this is increased reliance on opening bowlers, as, by their nature, they are typically perceived as being the most capable of taking wickets (Petersen et al., 2008). Another probable explanation for this is the restrictions placed on competition format, with limited overs cricket restricting the number of overs bowled to either a maximum of 10-overs (OD) or 4-overs (T20), respectively (Olivier et al., 2016; Orchard et al., 2015). A further consideration is the nature of the “block” approach to fixture scheduling, with the majority of County Championship competition occurring in the first and last quarters of the season.

The findings of this chapter were able to detail descriptive fast bowling competition loads, highlighting significant differences accounting for monthly variation, competition format and bowler classification, respectively. Despite the large emphasis placed on fast bowling loads in this chapter and associated injury from existing literature, data pertaining to cricket locomotion for determining physiological measures was absent. Therefore, the remaining experimental chapters (Chapters 5 – 7) utilised MEMS technology to quantify player movement patterns and activity profiles (external training load) and physiological and psycho-biological responses (internal training load) to characterise limited overs one-day cricket, which has been shown to produce the least variability between descriptive fast bowling loads.

While we sought to investigate limited overs cricket and were able to show that, generally, competition bowling loads did not differ between opening and support fast bowlers, the complex and intermittent characteristics typically experienced in competition are unstable and subject to variation between matches (Gregson et al., 2010; Kempton et al., 2014; McLaren et al., 2016). While typical movement patterns

and the associated between-match variability has already been described (Petersen, Portus, et al., 2009; Petersen et al., 2010), this data is limited to Australian national cricketers. Moreover, given the recent global development of domestic T20 competitions, the variability of physical performance and bowling demands is likely to differ from this published data. In addition to adding to the existing literature by examining between-match variability, this chapter was able to provide a novel approach to exploring within-match between-over variability.

The results from Chapter 5 indicate that high-speed locomotive activity (high-speed running distance [$\geq 14.4 \text{ km}\cdot\text{h}^{-1}$], total sprint distance and number of sprints performed) is highly variable, both between-matches and within-match between-overs. However, comparatively total distance (TD) and PlayerLoad™ (PL) were more stable both between- and within-match between-over. Firstly, we reported similar between-match variability for high-speed locomotive activities reported in cricket and other team sports (Gastin, McLean, et al., 2013; Gregson et al., 2010; Kempton et al., 2014; McLaren et al., 2016; Petersen et al., 2010). Moreover, we were able to indicate that changes in more global measures in match loads may be interpreted with more accuracy than high-speed locomotive measures. While we demonstrated a similar percentage contribution of time spent sprinting with the existing literature, we also identified large discrepancies between descriptive match data, specifically TD covered (Petersen, Portus, et al., 2009). Given the similarities in sample size and playing standard, this is somewhat surprising. However, it may be a consequence of the marked worldwide change in T20 cricket (McNamara et al., 2016) or the increased number of match observations than previously cited (Petersen, Portus, et al., 2009).

Despite showing a high degree of variability among high-speed locomotive activities, when uniquely exploring the data using within-match between-over, we

were able to demonstrate marked reductions in both high-speed locomotion and more global measures of external training load (TD and PL), respectively. Importantly, by examining the data in this way, it may potentially exclude constraints imposed by fielding position, which may be responsible for the differences in between-match variability (Kempton et al., 2015). As a result of these findings, practitioners may be able to increase the specificity when designing and planning appropriate training sessions, that aim to replicate physical performance and match demands (Kempton et al., 2014; McLaren et al., 2016), specifically related to fast bowling.

In light of these findings, practitioners may wish to also further consider the increased match demands of one-day 50-over cricket. Consequently, 50-over cricket results in increases to both match duration (≤ 3.5 h) and fast bowling workloads (≤ 10 -overs) (Olivier et al., 2016; Orchard et al., 2015). Specifically, a fast bowler could increase their bowling workload from a maximum of 24 (in T20) to a maximum of 60 repetitive high-intensity bowling episodes incorporating the run-up, followed by upper- and lower-body actions (classified as acceleration/deceleration efforts) interspersed with periods of lower-intensity fielding activities (J. A. Johnstone et al., 2014; Minett et al., 2012b; Noakes & Durandt, 2000; Orchard et al., 2009). In light of the aforementioned increased match demands, we sought to further quantify between-match variability in external training load (derived from MEMS). Furthermore, given the increased eccentric contributions of these muscle actions during fast bowling, we further sought to quantify NMF following one-day 50-over cricket.

Fatigue has been described as an acute impairment of performance that includes a reduction in the maximal voluntary force production by a muscle or muscle group and/or an increase in the perceived effort to exert a desired force or power (Gandevia,

2001; Rampinini et al., 2011). An accumulation of fatigue or incomplete recovery can have a large influence on performance, especially during periods of regular competition (McLean et al., 2010). One particular facet of fatigue that has gained increasing interest among sport scientists and practitioners is NMF, which is often quantified using a CMJ protocol. Despite its popularity within other field-based team sports, within cricket, specifically fast bowling, CMJ data is limited to spells of simulated fast bowling (Duffield et al., 2009; Minett et al., 2012a, 2012b). Therefore, by quantifying the demands imposed on fast bowlers during match play (number of overs bowled), we provided a novel insight into the nature of and time-course of NMF during both a single match and an entire season, while exploring any associated relationships.

The results from Chapter 6 indicate very large reductions in CMJ flight-time following one-day 50-over cricket. In general, these findings agree with data from other team sports showing significant reductions in CMJ performance following competition (Cormack, Newton, & McGuigan, 2008; C. P. McLellan et al., 2011b; Wehbe et al., 2015). Interestingly, when these data were analysed dependent on the outcome of the “coin toss”, significant reductions in CMJ flight-time were only observed on those occasions where bowlers bowled first (not after tea [2nd]). Furthermore, when CMJ data were adjusted in accordance with fast bowling workloads, results indicated moderate to large reductions in CMJ flight-time in both MODERATE (5-8 overs) and HIGH (9-12 overs) workload groups. This is the first study to show notable reductions in CMJ performance following limited overs cricket, conflicting with earlier research (Duffield et al., 2009; Minett et al., 2012a, 2012b). However, it is important to acknowledge that, in these studies, bowlers typically bowled 6-overs in a simulated environment and therefore the bowling loads may not

truly reflect the demands of competition. A unique part of this experimental chapter was to explore the relationships between changes in CMJ flight-time and both internal and external training load measures. It was found that RPE and sRPE were the only measures to significantly correlate with changes in CMJ flight-time. However, these were inverse relationships and may be a result of the concept known as regression to the mean. Regression to the mean occurs when the initial pre-test value is at a high extreme with post-test values less so (Nevill et al., 2004). This phenomenon may contribute to partly explain our findings and supports those of Shephard, Hamm, Mertens, Beyene, and Kavanagh (2002) who investigated the influence of initial fitness in response to cardiac rehabilitation.

Furthermore, the results from this chapter extended our earlier work and add to the existing literature by quantifying descriptive external training load data (derived from MEMS) and also reported on the between-match variability of one-day limited overs cricket. Despite adding to the existing literature, we found conflicting findings, whereby the professional fast bowlers in this study covered less total distance at all speed thresholds than previously reported (Petersen et al., 2010; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009). This is somewhat surprising, given that some descriptive match data, playing time and overs bowled failed to substantially differ. Furthermore, we were able to show similar between-match variability in the MEMS data compared to our previous work and that of Petersen and colleagues (2009; 2010; 2011), concluding that TD displayed the least variability of all TL measures.

Effective monitoring strategies in cricket require tracking variables that are sensitive to physiological changes that accompany the stress of cricket fast bowling. As a result

of our previous work, we were able to identify that CMJ flight-time was able to detect changes in NMF as a result of match play and increasing fast bowling workloads. Therefore, it may be proposed that, by including a combination of biochemical, endocrine and perceptual markers, which have been shown in other team sports to be capable of identifying subtle changes in player fatigue and recovery status, this may aid an increased identification of fatigue in cricket. In an attempt to overcome the between-match variability from one-day limited overs cricket, we designed the final study to examine the neuromuscular, biochemical and endocrine responses to a laboratory-controlled cricket simulation (CA-AIS fast-bowling skills test) (Duffield et al., 2009; M. Portus et al., 2010). This approach enables the determination of “dose-response” relationships with standardised locomotor and fast bowling workloads.

As previously discussed, the demands of cricket and requirements of fast bowlers to repeatedly engage in prolonged eccentric muscle contractions, may collectively result in EIMD (Noakes & Durandt, 2000; Twist & Eston, 2005). Therefore, by including analysis of biochemical and endocrine parameters (CK, UA, Urea and sCort), we were able to facilitate a greater understating of EIMD and stress attributed to fast bowling. We were able to extend our earlier research by similarly exploring associations between fast bowling training loads, biochemical, endocrine and perceptual fatigue measures immediately (+0.5-h) and acutely (+24-h) following bouts of simulated fast bowling.

The results from Chapter 7 showed that both immediately (+0.5-h) and 24-h post simulation, CMJ performance was significantly impaired versus pre-simulation values (- 0.5-h). Furthermore, when comparisons were made between both post-simulation values (+ 0.5-h vs. + 24-h), we also showed impaired CMJ performance.

Collectively, these findings indicate that, following simulated fast bowling, players still experienced notable NMF for up to 24-h post-simulation, which agrees with existing team sport literature (Cormack, Newton, & McGuigan, 2008; Wehbe et al., 2015). Again, these findings tend to disagree with earlier research (Duffield et al., 2009; Minett et al., 2012a, 2012b), which is surprising, as this study also used the same CA-AIS fast-bowling skills test. Furthermore, when we analysed CMJ performance to account for fast bowling workloads, we identified that CMJ flight-time typically decreased as a result of an increased number of overs bowled. Thus, we were able to identify that a “dose-response” relationship existed between NMF and fast bowling training loads.

In addition to the CMJ data, we also showed a similar pattern among the biochemical parameters, whereby plasma CK, UA and urea concentrations were all significantly elevated from pre-simulation, peaking at 24-h. Similarly, studies have also explored the CK response to simulated fast bowling, with results reaffirming our findings indicating an acute response (Lombard et al., 2012; Minett et al., 2012a, 2012b). Of all biochemical and endocrine measures, sCort typically displayed the largest significant differences between pre-simulation values and at both time points (+ 0.5-h and +24-h). To date, McNamara and co-workers (2013) are the only researchers to outline endocrine responses of cricketers. Despite this, they only provide a comparison between fast bowlers and non-fast bowlers. However, it is important to acknowledge that during both training and competition phases, fast bowlers tended to present significantly greater sCort concentrations than non-fast bowlers, which was attributed to the increased training load of fast bowlers.

As previously (see Chapter 6), we again explored relationships between changes in CMJ flight-time, MEMS performance and subjective data. However,

unlike before, we sought to explore the same relationships with additional biochemical (CK, UA and urea) and endocrine (sCort) measures. Firstly, these results identified that perceptual well-being was moderately correlated ($r = 0.38$; 90% CI 0.14 to 0.58) to changes in CMJ flight-time. Moreover, when this data was adjusted to the specific fast bowling workloads, the relationship was magnified ($r = 0.62$; 90% CI 0.14 to 0.68). Furthermore, when conducting the same analysis of biochemical and endocrine measures, we identified that CK appeared to be the primary biochemical marker to display multiple relationships with external (TD & PL) and internal (HREI, RPE & sRPE) training load parameters, both immediately and 24-h post simulation, respectively. Collectively, these findings support the monitoring of CMJ performance and both internal and external training load variables agreeing with data from both rugby league and Australian Rules Football (Hunkin et al., 2014; Oxendale et al., 2016; Young et al., 2012).

8.2. Conclusions

Understanding the typical fast bowling workloads, variability of training load measures and status of neuromuscular, biochemical and endocrine systems in professional cricket should be considered essential for sport scientists and practitioners alike. The significance of this is further reiterated by the widely accepted increased playing demands of the professional game. Firstly, this thesis is able to conclude that fast bowlers are inherently exposed to a high volume of matches, experiencing a high degree of between-match variability in high-speed running parameters. Furthermore, we identified that selected external training load measures (TD and PL) appear more stable and may be interpreted with greater accuracy. Ultimately, we are able to conclude that fast bowlers experience immediate and delayed symptoms of fatigue and

EIMD that persist in the days following competition. Moreover, if used properly, this data has the potential to influence practitioners and coaches into team selection, player preparation and/or recovery strategies.

8.3. Limitations

The aims of this thesis were to quantify descriptive fast bowling workloads, examine the practical application of both internal and external training load measures and explore the acute fatigue response to OD limited overs cricket, with special reference to fast bowling volumes. This section aims to address some of the potential limitations associated within the descriptive and experimental chapters, respectively.

Multiple studies have reported fast bowling workloads (including competition and training) and their association with injury (Dennis et al., 2003; Hulin et al., 2014; Olivier et al., 2016; Orchard et al., 2015; Orchard et al., 2009; Orchard et al., 2016). Despite this, this was not within the scope of this thesis. Unfortunately, this was the main limitation within Chapter 4. As a result of this, we may have failed to achieve a true account of the fast bowling loads and variation between opening and support bowlers. For example, some bowlers may have missed a competitive match or matches, did not bowl due to injury or illness, which was not controlled for. Moreover, it is important to acknowledge that data obtained for this thesis was predominately competition-derived workloads and thus we do not provide a true reflection of a fast bowler's overall training and competition workload.

One considerable limitation within this thesis, especially within Chapters 5 and 6, are the low subject numbers. Despite this limitation, it is important to acknowledge that fast bowlers typically account for 3 to 5 of the 11 players on each team

(McNamara et al., 2015a). Therefore, by providing an $n = 8$ (Chapter 5) and an $n = 6$ (Chapter 6), we can argue that the data collected provides an accurate reflection of player movement patterns associated with cricket competition and is unavoidable. Furthermore, while we acknowledge the low subject numbers, which in turn may underpower the statistical analysis, it is important to highlight that the fast bowlers recruited were competing professionally and thus we argue that the quality of the data surpasses the quantity. However, data were collected during all competitive T20 (Chapter 5) and one-day limited over fixtures (Chapter 6), respectively.

Recent advances in TMA have led to widespread use of GPS technologies within team sport settings, providing real-time analysis of player movement patterns (Cummins et al., 2013). These devices are currently manufactured with an array of sampling rates (1 Hz, 5 Hz, 10 Hz), with literature suggesting that a higher frequency rate provides greater validity for the measurement of distance covered. Furthermore, it has been highlighted that the reliability of GPS decreases with the increased movement speed (Cummins et al., 2013). The locomotive characteristics detailed in this thesis (Chapter 5 & 6) used a 5 Hz GPS system. The measurement error (TEM) for these GPS systems used for total distance, low-speed ($\leq 14.4 \text{ km}\cdot\text{h}^{-1}$) and high-speed ($\geq 14.4 \text{ km}\cdot\text{h}^{-1}$) running distance during simulated team sport activities is reported to be 2.0%, 4.3% and 10.8%, respectively (R. J. Johnston et al., 2012; Petersen, Pyne, Portus, & Dawson, 2009). Moreover, the GPS sampling frequency used in this study has been extensively cited in earlier cricket studies (Petersen et al., 2010; Petersen, Pyne, Portus, & Dawson, 2009; Petersen, Pyne, Dawson, et al., 2011; Petersen, Pyne, Portus, et al., 2011; Petersen, Pyne, Portus, Karppinen, et al., 2009) and, therefore, may aid in comparing descriptive locomotive data. Furthermore, while we acknowledge this limitation, we also presented data pertaining to both the number

of satellites available for signal transmission and mean HDOP, thus collectively supporting the accuracy and quality of signal (Jennings et al., 2010a; Waldron et al., 2011).

Despite all playing surfaces conforming to and meeting the requirements of The MCC Laws of Cricket (MCC, 2013), a further limitation within this thesis (Chapter 5 & 6) was that we failed to quantify the influence of a range of contextual factors contributing to the variability of match performance, namely opposition strength, match outcome, match location, player fitness and specific role within each match (Gregson et al., 2010; Kempton et al., 2014; Rampinini et al., 2007; Stronach et al., 2014).

It is possible that various biochemical and endocrine markers measured from both blood and saliva may assist in identifying the acute response and time-course recovery cycle (Twist & Highton, 2013). For example, there has been extensive discussion within the literature relating to an increase in CK and sCort being indicative of EIMD and stress following exercise. Despite its widespread use, the molecular mechanisms that result in the release of CK from the muscle into blood after exercise remain unclear (Baird et al., 2012). Moreover, as CK has been shown to have an extremely large individual variability (Coutts, Reaburn, Piva, & Rowsell, 2007; A. Scott et al., 2016; Twist & Highton, 2013) (see Chapter 7; Figure 7.2.), caution is required when interpreting the data, as it may only provide a general indication of EIMD. In an attempt to alleviate some limitations associated with CK, we sought to include the collection of sCort on the basis that it typically responds dependant on the type, intensity and duration of exercise (McLellan et al., 2010; P. Passelergue, Robert, & Lac, 1995). Furthermore, it is important to consider the methodological differences and cost implications associated with the collection of these parameters, which may

partly explain the discrepancy between the biochemical and endocrine markers in this study and that of others.

Although, perceptual well-being was collected as a secondary surrogate measure, it is worth acknowledging that self-reporting may be deemed a limitation, as the reliability may be compromised, if bowlers were to report dishonest values. Moreover, implementing more stringent post simulation (+ 24 h) control measures (i.e. standardised recovery protocol) could have enhanced the robustness of the questionnaire. In an attempt to prevent some associated limitations, bowlers were familiarised with the questionnaire and were educated on its role within the study and were encouraged to report honest values.

Despite these limitations, we adopted a “real world” approach to research, collecting the majority of data from professional fast bowlers (Chapters 4, 5 & 6), which we hope provided data that is high in ecological validity.

8.4. Future Research Recommendations

The review of the literature and the novel findings of this thesis suggest that research into the quantification of training load and fatigue associated with cricket, especially amongst fast bowlers, is still in its infancy. Anecdotally and as a result of this thesis, it is clear that fixture scheduling and fast bowling workloads appear to be a fundamental consideration for those working in cricket. Therefore, there are a number of avenues that warrant further investigation.

It is widely accepted that professional athletes need to train at high-intensity to elicit improvements in skill and physical fitness qualities. It is also well understood that too much high-intensity training without adequate recovery is detrimental to performance (McLean et al., 2010; Smith, 2003). Moreover, during a professional

cricket season, players compete in a high volume of matches ($n = \sim 100$ days) per season, across multiple match formats, resulting in large, irregular variations in competition loads in short time frames (J. A. Johnstone et al., 2014; Noakes & Durandt, 2000; Orchard et al., 2010; Orchard et al., 2009). To date, research exploring the cumulative effect of training, competition, fixture congestion and travel, that are all associated with professional cricket, is sparse. As such, it would appear important to quantify the occurrence of cumulative fatigue and perceptual well-being associated with professional cricket both internationally and domestically.

As alluded to previously (see Section 8.3.), GPS devices are currently manufactured with an array of sampling rates, with literature suggesting that a higher sampling frequency provides greater validity for the measurement of distance covered. Therefore, the future recommendations based on GPS data collected during this thesis would be to consider collecting locomotive data at 10 Hz. Importantly, these devices have been shown to be capable of measuring the smallest worthwhile change in acceleration, deceleration and reduce the errors associated with high-speed locomotive activity (Cummins et al., 2013; Dellaserra et al., 2014). Most recently, 15 Hz GPS has been introduced. However, the 15 Hz sampling rate is derived from the original 10 Hz GPS and is supplemented with the use of tri-axial accelerometry (Aughey, 2011; R. J. Johnston, Watsford, Kelly, Pine, & Spurrs, 2014). As a result of this integrated tri-axial accelerometry, an accelerometer derived modified vector magnitude algorithm, termed PL, is becoming increasingly cited within the team sport literature (Barrett et al., 2014; Barrett et al., 2015; Boyd et al., 2011, 2013; B. R. Scott et al., 2013). Despite using PL in this thesis, research is still in its infancy in cricket (McNamara et al., 2015a, 2015b) and thus we suggest further research exploring its practical applications.

8.5. Practical Applications

This thesis was conducted predominately with professional medium to fast bowlers, allowing for several important practical findings to be made, that are relevant to coaches and practitioners working in the professional game. Similar practical applications to the amateur game may warrant further investigation.

- There are clear differences in fast bowling workloads between opening and support bowlers.
- Adopting an individualised approach to these variable bowling loads, coaches and practitioners may wish to prescribe upper and lower bowling thresholds throughout differing stages of the competitive season.
- There are inherent difficulties in using high-speed running parameters for conducting analysis of both T20 and OD limited overs cricket, due to the high degree of between-match variability.
- A possible solution to combat this is to explore the variability of global measures of external training load (TD and PL).
- Although TD may initially appear of interest, given its low degree of variability, its importance as a sport-specific dependent variable is questionable.
- A possible solution to combat this might be to focus specifically on within-match between-over analysis, as the variability in all external training load variables is reduced markedly.
- A further consideration is to utilise PL, as this displays a low degree of variability irrespective of analysis method and would allow coaches and

conditioning staff to be confident that this measure could accurately quantify the physical match demands.

- Researchers and practitioners should adopt specific statistical approaches (magnitude-based inferences) which use both between- and within-match CVs specific to their athlete population when considering training prescription.
- An easy to administer functional test of neuromuscular status can provide a useful insight into the fatigue and recovery status of high-level team sport athletes.
- CMJ flight-time was shown to be sensitive to detect NMF and the associated fluctuations in fast bowling workloads in both competition and laboratory-based simulated fast bowling.
- Combining descriptive performance variables, specifically the number of overs bowled, with CMJ flight-time, we were able to show increased sensitivity when assessing NMF and, therefore, offering an increased usefulness as a monitoring tool.
- By combining biochemical (CK) and endocrine (sCort) responses to performance, coaches and practitioners may be able to establish a more tangible identification of individual responses to periods of fast bowling.
- Psycho-biological measures (RPE) of internal training load provide a simple cost-effective monitoring tool that can provide information pertaining to an individual's exercise tolerance.
- Elevated CK appears to display an association with estimated TD covered and sRPE immediately following simulated fast bowling.

- Elevated CK shows further associations with descriptive simulation data (number of deliveries bowled and simulation duration) 24 h following simulated fast bowling.
- Elevated CK also shows associations with internal (HREI) and external (estimated TD and PL) training load up to 24 h following simulated fast bowling.
- Collectively, the monitoring of CK appears to offer a superior monitoring tool when seeking to explore the “dose-response” relationship between fast bowling and EIMD.

9. References

- Akubat, I., & Abt, G. (2011). Intermittent exercise alters the heart rate-blood lactate relationship used for calculating the training impulse (TRIMP) in team sport players. *Journal of Science and Medicine in Sport*, 14(3), 249-253. doi:10.1016/j.jsams.2010.12.003
- Akubat, I., Barrett, S., & Abt, G. (2014). Integrating the internal and external training loads in soccer. *International Journal of Sports Physiology and Performance*, 9(3), 457-462. doi:10.1123/ijsp.2012-0347
- Akubat, I., Patel, E., Barrett, S., & Abt, G. (2012). Methods of monitoring the training and match load and their relationship to changes in fitness in professional youth soccer players. *Journal of Sports Sciences*, 30(14), 1473-1480. doi:10.1080/02640414.2012.712711
- Alexiou, H., & Coutts, A. J. (2008). A comparison of methods used for quantifying internal training load in women soccer players. *International Journal of Sports Physiology and Performance*, 3(3), 320-330.
- Andersson, H., Raastad, T., Nilsson, J., Paulsen, G., Garthe, I., & Kadi, F. (2008). Neuromuscular fatigue and recovery in elite female soccer: effects of active recovery. *Medicine and Science in Sports and Exercise*, 40(2), 372-380. doi:10.1249/mss.0b013e31815b8497
- Arteaga, R., Dorado, C., & Calbet, J. C. J. (2000). Reliability of jumping performance in active men and women under different stretch loading conditions. *Journal of Sports Medicine and Physical Fitness*, 40(1), 26.
- Atkinson, G., & Nevill, A. M. (1998). Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Medicine*, 26(4), 217-238. doi:10.2165/00007256-199826040-00002

- Aughey, R. J. (2011). Applications of GPS technologies to field sports. *International Journal of Sports Physiology and Performance*, 6(3), 295-310.
- Bahnert, A., Norton, K., & Lock, P. (2012). Association between post-game recovery protocols, physical and perceived recovery, and performance in elite AFL players. *Journal of Science and Medicine in Sport*.
- Baird, M. F., Graham, S. M., Baker, J. S., & Bickerstaff, G. F. (2012). Creatine-kinase- and exercise-related muscle damage implications for muscle performance and recovery. *Journal of Nutrition and Metabolism*, 2012.
- Balsalobre-Fernández, C., Glaister, M., & Lockey, R. A. (2015). The validity and reliability of an iPhone app for measuring vertical jump performance. *Journal of Sports Sciences*, 33(15), 1574-1579.
- Balsalobre-Fernández, C., Tejero-González, C. M., & del Campo-Vecino, J. (2014). Relationships between training load, salivary cortisol responses and performance during season training in middle and long distance runners. *PloS One*, 9(8), e106066.
- Bangsbo, J. (1994). Energy demands in competitive soccer. *Journal of Sports Sciences*, 12 Spec No, S5-12.
- Banister, E. (1991). *Modeling elite athletic performance*.
- Banister, E., Calvert, T., Savage, M., & Bach, T. (1975). A systems model of training for athletic performance. *Australian Journal of Science and Medicine in Sport*, 7(3), 57-61.
- Barnett, A. (2006). Using recovery modalities between training sessions in elite athletes. *Sports Medicine*, 36(9), 781-796. doi:10.2165/00007256-200636090-00005

- Barrett, S., Midgley, A., & Lovell, R. (2014). PlayerLoad: reliability, convergent validity, and influence of unit position during treadmill running. *International Journal of Sports Physiology and Performance*, 9(6), 945-952. doi:10.1123/ijsp.2013-0418
- Barrett, S., Midgley, A. W., Towlson, C., Garrett, A., Portas, M., & Lovell, R. (2015). Within-Match PlayerLoad™ patterns during a simulated soccer match (SAFT90): potential implications for unit positioning and fatigue management. *International Journal of Sports Physiology and Performance*.
- Batterham, A. M., & Hopkins, W. G. (2006). Making Meaningful Inferences About Magnitudes. *International Journal of Sports Physiology and Performance*, 1(1), 50-57.
- Bengtsson, H., Ekstrand, J., & Hagglund, M. (2013). Muscle injury rates in professional football increase with fixture congestion: an 11-year follow-up of the UEFA Champions League injury study. *British Journal of Sports Medicine*, 47(12), 743-747. doi:10.1136/bjsports-2013-092383
- Bishop, D., Spencer, M., Duffield, R., & Lawrence, S. (2001). The validity of a repeated sprint ability test. *Journal of Science and Medicine in Sport*, 4(1), 19-29.
- Bishop, P. A., Jones, E., & Woods, A. K. (2008). Recovery from training: a brief review. *Journal of Strength and Conditioning Research*, 22(3), 1015-1024. doi:10.1519/JSC.0b013e31816eb518
- Bosco, C., Komi, P. V., Tihanyi, J., Fekete, G., & Apor, P. (1983). Mechanical power test and fiber composition of human leg extensor muscles. *European Journal of Applied Physiology and Occupational Physiology*, 51(1), 129-135.

- Bourdon, P. C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M. C., . . . Cable, N. T. (2017). Monitoring Athlete Training Loads: Consensus Statement. *International Journal of Sports Physiology and Performance*, *12*(Suppl 2), S2161-s2170. doi:10.1123/ijsp.2017-0208
- Boyd, L. J., Ball, K., & Aughey, R. J. (2011). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *International Journal of Sports Physiology and Performance*, *6*(3), 311-321.
- Boyd, L. J., Ball, K., & Aughey, R. J. (2013). Quantifying external load in Australian football matches and training using accelerometers. *International Journal of Sports Physiology and Performance*, *8*(1), 44-51.
- Bradley, W. J., Cavanagh, B. P., Douglas, W., Donovan, T. F., Morton, J. P., & Close, G. L. (2015). Quantification of training load, energy intake, and physiological adaptations during a rugby preseason: a case study from an elite European rugby union squad. *Journal of Strength and Conditioning Research*, *29*(2), 534-544. doi:10.1519/JSC.0000000000000631
- Brancaccio, P., Maffulli, N., & Limongelli, F. M. (2007). Creatine kinase monitoring in sport medicine. *British Medical Bulletin*, *81*(1), 209.
- Brink, M. S., Nederhof, E., Visscher, C., Schmikli, S. L., & Lemmink, K. A. (2010). Monitoring load, recovery, and performance in young elite soccer players. *Journal of Strength and Conditioning Research*, *24*(3), 597-603. doi:10.1519/JSC.0b013e3181c4d38b
- Buchheit, M., Racinais, S., Bilsborough, J. C., Bourdon, P. C., Voss, S. C., Hocking, J., . . . Coutts, A. J. (2013). Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players.

Journal of Science and Medicine in Sport, 16(6), 550-555.

doi:10.1016/j.jsams.2012.12.003

Burgess, D., Naughton, G., & Norton, K. (2012). Quantifying the gap between under 18 and senior AFL football: 2003 and 2009. *International Journal of Sports Physiology and Performance*, 7(1), 53-58.

Burnett, A. F., Elliott, B. C., & Marshall, R. N. (1995). The effect of a 12-over spell on fast bowling technique in cricket. *Journal of Sports Sciences*, 13(4), 329-341. doi:10.1080/02640419508732247

Cairns, S. P., Knicker, A. J., Thompson, M. W., & Sjogaard, G. (2005). Evaluation of models used to study neuromuscular fatigue. *Exercise and Sport Sciences Reviews*, 33(1), 9-16.

Carling, C., Gregson, W., McCall, A., Moreira, A., Wong del, P., & Bradley, P. S. (2015). Match running performance during fixture congestion in elite soccer: research issues and future directions. *Sports Medicine*, 45(5), 605-613. doi:10.1007/s40279-015-0313-z

Carling, C., Le Gall, F., & Dupont, G. (2012). Are physical performance and injury risk in a professional soccer team in match-play affected over a prolonged period of fixture congestion? *International Journal of Sports Medicine*, 33(1), 36-42. doi:10.1055/s-0031-1283190

Carling, C., McCall, A., Le Gall, F., & Dupont, G. (2016). The impact of short periods of match congestion on injury risk and patterns in an elite football club. *British Journal of Sports Medicine*, 50(12), 764-768. doi:10.1136/bjsports-2015-095501

Carling, C., Orhant, E., & LeGall, F. (2010). Match injuries in professional soccer: inter-seasonal variation and effects of competition type, match congestion and

- positional role. *International Journal of Sports Medicine*, 31(4), 271-276.
doi:10.1055/s-0029-1243646
- Casamichana, D., Castellano, J., Calleja, J., Román, J. S., & Castagna, C. (2012). Relationship Between Indicators of Training Load in Soccer Players. *Journal of Strength and Conditioning Research*.
- Chevion, S., Moran, D. S., Heled, Y., Shani, Y., Regev, G., Abbou, B., . . . Epstein, Y. (2003). Plasma antioxidant status and cell injury after severe physical exercise. *Proceedings of the National Academy of Sciences*, 100(9), 5119-5123. doi:10.1073/pnas.0831097100
- Christie, C. J.-A. (2012). *The Physical Demands of Batting and Fast Bowling in Cricket*: INTECH Open Access Publisher.
- Clarkson, P. M., & Ebbeling, C. (1988). Investigation of serum creatine kinase variability after muscle-damaging exercise. *Clinical Science*, 75(3), 257-261. doi:10.1042/cs0750257
- Claudino, J. G., Cronin, J., Mezencio, B., McMaster, D. T., McGuigan, M., Tricoli, V., . . . Serrao, J. C. (2016). The countermovement jump to monitor neuromuscular status: A meta-analysis. *Journal of Science and Medicine in Sport*. doi:10.1016/j.jsams.2016.08.011
- Coelho, D. B., Morandi, R. F., Melo, M. A. A. d., & Silami-Garcia, E. (2011). Creatine kinase kinetics in professional soccer players during a competitive season. *Revista Brasileira de Cineantropometria & Desempenho Humano*, 13(3), 189-194.
- Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*: Academic press.

- Cormack, S. J., Mooney, M. G., Morgan, W., & McGuigan, M. R. (2013). Influence of neuromuscular fatigue on accelerometer load in elite Australian football players. *International Journal of Sports Physiology and Performance*, 8(4), 373-378.
- Cormack, S. J., Newton, R. U., & McGuigan, M. R. (2008). Neuromuscular and endocrine responses of elite players to an Australian rules football match. *International Journal of Sports Physiology and Performance*, 3(3), 359-374.
- Cormack, S. J., Newton, R. U., McGuigan, M. R., & Cormie, P. (2008). Neuromuscular and endocrine responses of elite players during an Australian rules football season. *International Journal of Sports Physiology and Performance*, 3(4), 439-453.
- Cormack, S. J., Newton, R. U., McGuigan, M. R., & Doyle, T. L. A. (2008). Reliability of measures obtained during single and repeated countermovement jumps. *International Journal of Sports Physiology and Performance*, 3(2), 131-144.
- Coutts, A. J., & Duffield, R. (2010). Validity and reliability of GPS devices for measuring movement demands of team sports. *Journal of Science and Medicine in Sport*, 13(1), 133-135. doi:10.1016/j.jsams.2008.09.015
- Coutts, A. J., Reaburn, P., Piva, T. J., & Rowsell, G. J. (2007). Monitoring for overreaching in rugby league players. *European Journal of Applied Physiology*, 99(3), 313-324. doi:10.1007/s00421-006-0345-z
- Coutts, A. J., Slattery, K. M., & Wallace, L. K. (2007). Practical tests for monitoring performance, fatigue and recovery in triathletes. *Journal of Science and Medicine in Sport*, 10(6), 372-381. doi:10.1016/j.jsams.2007.02.007

- Crewther, B., Lowe, T., Ingram, J., & Weatherby, R. P. (2010). Validating the salivary testosterone and cortisol concentration measures in response to short high-intensity exercise. *Journal of Sports Medicine and Physical Fitness*, 50(1), 85.
- Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Medicine*, 43(10), 1025-1042. doi:10.1007/s40279-013-0069-2
- Cunniffe, B., Proctor, W., Baker, J. S., & Davies, B. (2009). An evaluation of the physiological demands of elite rugby union using global positioning system tracking software. *Journal of Strength and Conditioning Research*, 23(4), 1195-1203. doi:10.1519/JSC.0b013e3181a3928b
- de Hoyo, M., Cohen, D. D., Sanudo, B., Carrasco, L., Alvarez-Mesa, A., Del Ojo, J. J., . . . Otero-Esquina, C. (2016). Influence of football match time-motion parameters on recovery time course of muscle damage and jump ability. *Journal of Sports Sciences*, 34(14), 1363-1370. doi:10.1080/02640414.2016.1150603
- De Vries, J., Michielsen, H. J., & Van Heck, G. L. (2003). Assessment of fatigue among working people: a comparison of six questionnaires. *Occupational and Environmental Medicine*, 60(suppl 1), i10-i15.
- Dellal, A., Lago-Penas, C., Rey, E., Chamari, K., & Orhant, E. (2015). The effects of a congested fixture period on physical performance, technical activity and injury rate during matches in a professional soccer team. *British Journal of Sports Medicine*, 49(6), 390-394. doi:10.1136/bjsports-2012-091290
- Dellaserra, C. L., Gao, Y., & Ransdell, L. (2014). Use of integrated technology in team sports: a review of opportunities, challenges, and future directions for athletes.

Journal of Strength and Conditioning Research, 28(2), 556-573.
doi:10.1519/JSC.0b013e3182a952fb

Dennis, R. J., Farhart, P., Clements, M., & Ledwidge, H. (2004). The relationship between fast bowling workload and injury in first-class cricketers: a pilot study. *Journal of Science and Medicine in Sport*, 7(2), 232-236. doi:10.1016/S1440-2440(04)80014-8

Dennis, R. J., Farhart, P., Goumas, C., & Orchard, J. (2003). Bowling workload and the risk of injury in elite cricket fast bowlers. *Journal of Science and Medicine in Sport*, 6(3), 359-367.

Dennis, R. J., Finch, C. F., & Farhart, P. J. (2005). Is bowling workload a risk factor for injury to Australian junior cricket fast bowlers? *British Journal of Sports Medicine*, 39(11), 843-846; discussion 843-846.
doi:10.1136/bjism.2005.018515

Devlin, L. H., Fraser, S. F., Barras, N. S., & Hawley, J. A. (2001). Moderate levels of hypohydration impairs bowling accuracy but not bowling velocity in skilled cricket players. *Journal of Science and Medicine in Sport*, 4(2), 179-187.

Duffield, R., Carney, M., & Karppinen, S. (2009). Physiological responses and bowling performance during repeated spells of medium-fast bowling. *Journal of Sports Sciences*, 27(1), 27-35. doi:10.1080/02640410802298243

Duffield, R., & Drinkwater, E. J. (2008). Time-motion analysis of Test and One-Day international cricket centuries. *Journal of Sports Sciences*, 26(5), 457-464.
doi:10.1080/02640410701644026

Duffield, R., Murphy, A., Snape, A., Minett, G. M., & Skein, M. (2012). Post-match changes in neuromuscular function and the relationship to match demands in

- amateur rugby league matches. *Journal of Science and Medicine in Sport*, 15(3), 238-243. doi:10.1016/j.jsams.2011.10.003
- Dupont, G., Nedelec, M., McCall, A., McCormack, D., Berthoin, S., & Wisloff, U. (2010). Effect of 2 soccer matches in a week on physical performance and injury rate. *The American Journal of Sports Medicine*, 38(9), 1752-1758. doi:10.1177/0363546510361236
- Edwards, S. (1994). The heart rate monitor book. *Medicine and Science in Sports and Exercise*, 26(5), 647.
- Ekstrand, J., Walden, M., & Hagglund, M. (2004). A congested football calendar and the wellbeing of players: correlation between match exposure of European footballers before the World Cup 2002 and their injuries and performances during that World Cup. *British Journal of Sports Medicine*, 38(4), 493-497. doi:10.1136/bjism.2003.009134
- Elloumi, M., Maso, F., Michaux, O., Robert, A., & Lac, G. (2003). Behaviour of saliva cortisol [C], testosterone [T] and the T/C ratio during a rugby match and during the post-competition recovery days. *European Journal of Applied Physiology*, 90(1), 23-28. doi:10.1007/s00421-003-0868-5
- Fallowfield, J. L., Hale, B. J., & Wilkinson, D. M. (2005). *Using statistics in sport and exercise science research*: Lotus Pub.
- Fisher, R. N., McLellan, C. P., & Sinclair, W. H. (2016). The validity and reliability for a salivary cortisol point of care test. *Journal of Athletic Enhancement*, 2015.
- Fletcher, J. G. (1955). Calories and cricket. *Lancet*, 268(6875), 1165-1166.
- Fossati, P., Prencipe, L., & Berti, G. (1980). Use of 3,5-Dichloro-2-Hydroxybenzenesulfonic Acid-4-Aminophenazone Chromogenic System in

- Direct Enzymic Assay of Uric-Acid in Serum and Urine. *Clinical Chemistry*, 26(2), 227-231.
- Foster, C., Florhaug, J. A., Franklin, J., Gottschall, L., Hrovatin, L. A., Parker, S., . . . Dodge, C. (2001). A new approach to monitoring exercise training. *Journal of Strength and Conditioning Research*, 15(1), 109-115.
- Fowles, J. R. (2006). Technical issues in quantifying low-frequency fatigue in athletes. *International Journal of Sports Physiology and Performance*, 1(2), 169-171.
- Gandevia, S. C. (2001). Spinal and supraspinal factors in human muscle fatigue. *Physiological Reviews*, 81(4), 1725-1789.
- Gastin, P. B., McLean, O., Spittle, M., & Breed, R. V. (2013). Quantification of tackling demands in professional Australian football using integrated wearable athlete tracking technology. *Journal of Science and Medicine in Sport*, 16(6), 589-593. doi:10.1016/j.jsams.2013.01.007
- Gastin, P. B., Meyer, D., & Robinson, D. (2013). Perceptions of wellness to monitor adaptive responses to training and competition in elite Australian football. *Journal of Strength and Conditioning Research*, 27(9), 2518-2526. doi:10.1519/JSC.0b013e31827fd600
- Gathercole, R. J., Sporer, B. C., Stellingwerff, T., & Sleivert, G. G. (2015a). Alternative countermovement-jump analysis to quantify acute neuromuscular fatigue. *International Journal of Sports Physiology and Performance*, 10(1), 84-92.
- Gathercole, R. J., Sporer, B. C., Stellingwerff, T., & Sleivert, G. G. (2015b). Comparison of the capacity of different jump and sprint field tests to detect neuromuscular fatigue. *Journal of Strength and Conditioning Research*, 29(9), 2522-2531. doi:10.1519/JSC.0000000000000912

- Gleeson, M. (2002). Biochemical and immunological markers of overtraining. *Journal of Sports Science and Medicine*, 1(2), 31-41.
- Gore, C. J., Bourdon, P. C., Woolford, S. M., & Pederson, D. G. (1993). Involuntary dehydration during cricket. *International Journal of Sports Medicine*, 14(7), 387-395. doi:10.1055/s-2007-1021197
- Gravetter, F. J., & Wallnau, L. B. (1999). Essentials of statistics for the behavioral sciences . Pacific Grove, CA: Brooks. *Cole Publishing Company*, 10, 0278-7393.0231.
- Gregson, W., Drust, B., Atkinson, G., & Salvo, V. D. (2010). Match-to-match variability of high-speed activities in premier league soccer. *International Journal of Sports Medicine*, 31(4), 237-242. doi:10.1055/s-0030-1247546
- Guilhem, G., Hanon, C., Gendreau, N., Bonneau, D., Guével, A., & Chennaoui, M. (2015). Salivary hormones response to preparation and pre-competitive training of world-class level athletes. *Frontiers in Physiology*, 6.
- Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Medicine*, 44 Suppl 2(2), S139-147. doi:10.1007/s40279-014-0253-z
- Haneishi, K., Fry, A. C., Moore, C. A., Schilling, B. K., Li, Y., & Fry, M. D. (2007). Cortisol and stress responses during a game and practice in female collegiate soccer players. *Journal of Strength and Conditioning Research*, 21(2), 583-588.
- Hartmann, U., & Mester, J. (2000). Training and overtraining markers in selected sport events. *Medicine and Science in Sports and Exercise*, 32(1), 209.
- Hayes, L. D., Grace, F. M., Baker, J. S., & Sculthorpe, N. (2015). Exercise-induced responses in salivary Testosterone, Cortisol, and their ratios in men: a meta-analysis. *Sports Medicine*, 45(5), 713-726. doi:10.1007/s40279-015-0306-y

- Hill-Haas, S. V., Dawson, B. T., Coutts, A. J., & Rowsell, G. J. (2009). Physiological responses and time–motion characteristics of various small-sided soccer games in youth players. *Journal of Sports Sciences*, 27(1), 1-8.
- Hoffman, J. R., Maresh, C. M., Newton, R. U., Rubin, M. R., French, D. N., Volek, J. S., . . . Kraemer, W. J. (2002). Performance, biochemical, and endocrine changes during a competitive football game. *Medicine and Science in Sports and Exercise*, 34(11), 1845-1853. doi:10.1249/01.MSS.0000035373.26840.F8
- Hooper, S. L., & Mackinnon, L. T. (1995). Monitoring overtraining in athletes. Recommendations. *Sports Medicine*, 20(5), 321-327.
- Hopkins, W. G. (2000). Measures of reliability in sports medicine and science. *Sports Medicine*, 30(1), 1-15. doi:10.2165/00007256-200030010-00001
- Hopkins, W. G. (2004). How to interpret changes in an athletic performance test. *Sportscience*, 8(1), 1-7.
- Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, 41(1), 3-13. doi:10.1249/MSS.0b013e31818cb278
- Hulin, B. T., Gabbett, T. J., Blanch, P., Chapman, P., Bailey, D., & Orchard, J. W. (2014). Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *British Journal of Sports Medicine*, 48(8), 708-712. doi:10.1136/bjsports-2013-092524
- Hunkin, S. L., Fahrner, B., & Gatin, P. B. (2014). Creatine kinase and its relationship with match performance in elite Australian Rules football. *Journal of Science and Medicine in Sport*, 17(3), 332-336. doi:10.1016/j.jsams.2013.05.005

- Hussain, N. (2014). Cricket fixture list schedule is punishing on the players and unfair on the fans paying. *Daily Mail*. Retrieved from <http://www.dailymail.co.uk/sport/cricket/article-2717056/NASSER-HUSSAIN-Cramming-cricket-matches-punishing-players-unfair-fans-paying-watch-it.html>
- Impellizzeri, F. M., Rampinini, E., Coutts, A. J., Sassi, A., & Marcora, S. M. (2004). Use of RPE-based training load in soccer. *Medicine and Science in Sports and Exercise*, 36(6), 1042-1047. doi:10.1249/01.Mss.0000128199.23901.2f
- Jennings, D., Cormack, S., Coutts, A. J., Boyd, L. J., & Aughey, R. J. (2010a). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *International Journal of Sports Physiology and Performance*, 5(3), 328-341.
- Jennings, D., Cormack, S., Coutts, A. J., Boyd, L. J., & Aughey, R. J. (2010b). Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology and Performance*, 5(4), 565-569.
- Johnston, M. J., Cook, C. J., Drake, D., Costley, L., Johnston, J. P., & Kilduff, L. P. (2016). The neuromuscular, biochemical, and endocrine responses to a single-session Vs. double-session training day in elite athletes. *Journal of Strength and Conditioning Research*, 30(11), 3098-3106. doi:10.1519/jsc.0000000000001423
- Johnston, R. D., Gabbett, T. J., Seibold, A. J., & Jenkins, D. G. (2014). Influence of physical contact on neuromuscular fatigue and markers of muscle damage following small-sided games. *Journal of Science and Medicine in Sport*, 17(5), 535-540. doi:10.1016/j.jsams.2013.07.018

- Johnston, R. D., Gibson, N. V., Twist, C., Gabbett, T. J., MacNay, S. A., & MacFarlane, N. G. (2013). Physiological responses to an intensified period of rugby league competition. *Journal of Strength and Conditioning Research*, 27(3), 643-654. doi:10.1519/JSC.0b013e31825bb469
- Johnston, R. J., Watsford, M. L., Austin, D. J., Pine, M. J., & Spurr, R. W. (2015). Movement demands and metabolic power comparisons between elite and subelite Australian footballers. *Journal of Strength and Conditioning Research*, 29(10), 2738-2744. doi:10.1519/JSC.0000000000000936
- Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J., & Spurr, R. W. (2014). Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *Journal of Strength and Conditioning Research*, 28(6), 1649-1655. doi:10.1519/JSC.0000000000000323
- Johnston, R. J., Watsford, M. L., Pine, M. J., Spurr, R. W., Murphy, A. J., & Pruyn, E. C. (2012). The validity and reliability of 5-Hz global positioning system units to measure team sport movement demands. *Journal of Strength and Conditioning Research*, 26(3), 758-765. doi:10.1519/JSC.0b013e318225f161
- Johnston, R. J., Watsford, M. L., Pine, M. J., Spurr, R. W., & Spurr, D. (2013). Assessment of 5 Hz and 10 Hz GPS units for measuring athlete movement demands. *International Journal of Performance Analysis in Sport*, 13(1), 262-274.
- Johnstone, J., ACS, M., Hughes, G., Watson, T., Ford, P., & Garrett, A. (2013). The Athletic Profile of Fast Bowling in Cricket: A review.
- Johnstone, J. A., & Ford, P. A. (2010). Physiologic profile of professional cricketers. *Journal of Strength and Conditioning Research*, 24(11), 2900-2907. doi:10.1519/JSC.0b013e3181bac3a7

- Johnstone, J. A., Hughes, G., Mitchell, A. C., Ford, P. A., Watson, T., Duffield, R., . . . Garrett, A. T. (2017). Accelerometry and heart rate responses of professional fast-medium bowlers in One-Day and Multi-Day cricket. *Journal of Sports Science and Medicine, 16*, 311-317.
- Johnstone, J. A., Mitchell, A. C., Hughes, G., Watson, T., Ford, P. A., & Garrett, A. T. (2014). The athletic profile of fast bowling in cricket: a review. *Journal of Strength and Conditioning Research, 28*(5), 1465-1473. doi:10.1519/JSC.0b013e3182a20f8c
- Jones, M. R., West, D. J., Harrington, B. J., Cook, C. J., Bracken, R. M., Shearer, D. A., & Kilduff, L. P. (2014). Match play performance characteristics that predict post-match creatine kinase responses in professional rugby union players. *BMC Sports Science, Medicine and Rehabilitation, 6*(1), 38. doi:10.1186/2052-1847-6-38
- Joyce, D., & Lewindon, D. (2014). *High-performance training for sports: Human Kinetics*.
- Karamizrak, S. O., Ergen, E., Töre, I. R., & Akgün, N. (1994). Changes in serum creatine kinase, lactate dehydrogenase and aldolase activities following supramaximal exercise in athletes. *The Journal of Sports Medicine and Physical Fitness, 34*(2), 141-146.
- Kempton, T., Sirotic, A. C., & Coutts, A. J. (2014). Between match variation in professional rugby league competition. *Journal of Science and Medicine in Sport, 17*(4), 404-407. doi:10.1016/j.jsams.2013.05.006
- Kempton, T., Sullivan, C., Bilsborough, J. C., Cordy, J., & Coutts, A. J. (2015). Match-to-match variation in physical activity and technical skill measures in

- professional Australian Football. *Journal of Science and Medicine in Sport*, 18(1), 109-113. doi:10.1016/j.jsams.2013.12.006
- Kim, J., & Lee, J. (2015). The relationship of creatine kinase variability with body composition and muscle damage markers following eccentric muscle contractions. *Journal of Exercise Nutrition and Biochemistry*, 19(2), 123-129. doi:10.5717/jenb.2015.15061910
- Kindermann, W. (1986). Overtraining—an expression of faulty regulated development. translated from. *Deutsche Zeitschrift Fur Sportmedizin*, 37, 238-245.
- Komi, P. V. (2000). Stretch-shortening cycle: a powerful model to study normal and fatigued muscle. *Journal of Biomechanics*, 33(10), 1197-1206.
- Kozey, S. L., Lyden, K., Howe, C. A., Staudenmayer, J. W., & Freedson, P. S. (2010). Accelerometer output and MET values of common physical activities. *Medicine and Science in Sports and Exercise*, 42(9), 1776.
- Kraemer, W. J., Spiering, B. A., Volek, J. S., Martin, G. J., Howard, R. L., Ratamess, N. A., . . . Maresh, C. M. (2009). Recovery From a National Collegiate Athletic Association Division I Football Game: Muscle Damage and Hormonal Status. *Journal of Strength and Conditioning Research*, 23(1), 2-10. doi:10.1519/JSC.0b013e31819306f2
- Larsson, P. (2003). Global Positioning System and Sport-Specific Testing. *Sports Medicine*, 33(15), 1093-1101. doi:10.2165/00007256-200333150-00002
- Lombard, W. P., Muir, G. A., & Mckune, A. J. (2012). Minimal changes in indirect markers of muscle damage after an acute bout of indoor pre-season fast bowling. *South African Journal for Research in Sport, Physical Education and Recreation*, 34(2), 105-114.

- Love, S., Aytar, A., Bush, H., & Uhl, T. L. (2010). Descriptive analysis of pitch volume in southeastern conference baseball pitchers. *North American Journal of Sports Physical Therapy*, 5(4), 194-200.
- Lovell, R., & Abt, G. (2012). Individualisation of Time-Motion Analysis: A Case-Cohort Example. *International Journal of Sports Physiology and Performance*.
- Lovell, R., Midgley, A., Barrett, S., Carter, D., & Small, K. (2013). Effects of different half-time strategies on second half soccer-specific speed, power and dynamic strength. *Scandinavian Journal of Medicine and Science in Sports*, 23(1), 105-113.
- MacLeod, H., Morris, J., Nevill, A., & Sunderland, C. (2009). The validity of a non-differential global positioning system for assessing player movement patterns in field hockey. *Journal of Sports Sciences*, 27(2), 121-128.
- Manzi, V., Bovenzi, A., Franco Impellizzeri, M., Carminati, I., & Castagna, C. (2013). Individual training-load and aerobic-fitness variables in premiership soccer players during the precompetitive season. *Journal of Strength and Conditioning Research*, 27(3), 631-636. doi:10.1519/JSC.0b013e31825dbd81
- Manzi, V., Iellamo, F., Impellizzeri, F., D'Ottavio, S., & Castagna, C. (2009). Relation between individualized training impulses and performance in distance runners. *Medicine and Science in Sports and Exercise*, 41(11), 2090-2096. doi:10.1249/MSS.0b013e3181a6a959
- Markovic, G., Dizdar, D., Jukic, I., & Cardinale, M. (2004). Reliability and factorial validity of squat and countermovement jump tests. *Journal of Strength and Conditioning Research*, 18(3), 551-555.

- Martin, A. (2016). England heading for Dubai R&R and hoping to refresh for final two Tests. *The Guardian* Retrieved from <https://www.theguardian.com/sport/2016/nov/29/england-dubai-tests-india-break-alastair-cook>
- MCC. (2013). The Laws of Cricket. <http://www.lords.org/laws-and-spirit/laws-of-cricket/>, 1 - 63. Retrieved from
- McGuigan, M. (2017). *Monitoring training and performance in athletes: Human Kinetics*.
- McLaren, S. J., Weston, M., Smith, A., Cramb, R., & Portas, M. D. (2016). Variability of physical performance and player match loads in professional rugby union. *Journal of Science and Medicine in Sport*, 19(6), 493-497. doi:10.1016/j.jsams.2015.05.010
- McLean, B. D., Coutts, A. J., Kelly, V., McGuigan, M. R., & Cormack, S. J. (2010). Neuromuscular, endocrine, and perceptual fatigue responses during different length between-match microcycles in professional rugby league players. *International Journal of Sports Physiology and Performance*, 5(3), 367-383.
- McLellan, C. P., & Lovell, D. I. (2012). Neuromuscular responses to impact and collision during elite rugby league match play. *Journal of Strength and Conditioning Research*, 26(5), 1431-1440. doi:10.1519/JSC.0b013e318231a627
- McLellan, C. P., Lovell, D. I., & Gass, G. C. (2010). Creatine Kinase and Endocrine Responses of Elite Players Pre, During, and Post Rugby League Match Play. *Journal of Strength and Conditioning Research*, 24(11), 2908-2919. doi:10.1519/JSC.0b013e3181c1fcb1

- McLellan, C. P., Lovell, D. I., & Gass, G. C. (2011). Biochemical and Endocrine Responses to Impact and Collision During Elite Rugby League Match Play. *The Journal of Strength & Conditioning Research*, 25(6), 1553-1562. doi:10.1519/JSC.0b013e3181db9bdd
- McLellan, C. P., Lovell, D. I., & Gass, G. C. (2011a). Biochemical and Endocrine Responses to Impact and Collision During Elite Rugby League Match Play. *Journal of Strength and Conditioning Research*, 25(6), 1553-1562. doi:10.1519/JSC.0b013e3181db9bdd
- McLellan, C. P., Lovell, D. I., & Gass, G. C. (2011b). Markers of postmatch fatigue in professional Rugby League players. *Journal of Strength and Conditioning Research*, 25(4), 1030-1039. doi:10.1519/JSC.0b013e3181cc22cc
- McNamara, D. J., Gabbett, T. J., Chapman, P., Naughton, G., & Farhart, P. (2015a). The validity of microensors to automatically detect bowling events and counts in cricket fast bowlers. *International Journal of Sports Physiology and Performance*, 10(1), 71-75. doi:10.1123/ijsp.2014-0062
- McNamara, D. J., Gabbett, T. J., Chapman, P., Naughton, G., & Farhart, P. (2015b). Variability of PlayerLoad™, bowling velocity and performance execution in fast bowlers across repeated bowling spells. *International Journal of Sports Physiology and Performance*.
- McNamara, D. J., Gabbett, T. J., & Naughton, G. (2016). Assessment of workload and its effects on performance and injury in elite cricket fast bowlers. *Sports Medicine*. doi:10.1007/s40279-016-0588-8
- McNamara, D. J., Gabbett, T. J., Naughton, G., Farhart, P., & Chapman, P. (2013). Training and competition workloads and fatigue responses of elite junior

- cricket players. *International Journal of Sports Physiology and Performance*, 8(5), 517-526.
- Michalsik, L. B. (2004). Analysis of working demands of Danish handball players *What's Going on in the Gym?* : Forlaget Underskoven.
- Minett, G. M., Duffield, R., Kellett, A., & Portus, M. (2012a). Effects of mixed-method cooling on recovery of medium-fast bowling performance in hot conditions on consecutive days. *Journal of Sports Sciences*, 30(13), 1387-1396. doi:10.1080/02640414.2012.709267
- Minett, G. M., Duffield, R., Kellett, A., & Portus, M. (2012b). Mixed-method pre-cooling reduces physiological demand without improving performance of medium-fast bowling in the heat. *Journal of Sports Sciences*, 30(9), 907-915. doi:10.1080/02640414.2012.679677
- Mohr, M., Krstrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of Sports Sciences*, 21(7), 519-528. doi:10.1080/0264041031000071182
- Montgomery, P. G., Pyne, D. B., & Minahan, C. L. (2010). The physical and physiological demands of basketball training and competition. *International Journal of Sports Physiology and Performance*, 5(1), 75-86.
- Mooney, M. G., Cormack, S., O'Brien B, J., Morgan, W. M., & McGuigan, M. (2013). Impact of neuromuscular fatigue on match exercise intensity and performance in elite Australian football. *Journal of Strength and Conditioning Research*, 27(1), 166-173. doi:10.1519/JSC.0b013e3182514683
- Mooney, M. G., O'Brien, B., Cormack, S., Coutts, A., Berry, J., & Young, W. (2011). The relationship between physical capacity and match performance in elite

- Australian football: a mediation approach. *Journal of Science and Medicine in Sport*, 14(5), 447-452. doi:10.1016/j.jsams.2011.03.010
- Nevill, A., Holder, R., Atkinson, G., & Copas, J. (2004). The dangers of reporting spurious regression to the mean. *Journal of Sports Sciences*, 22(9), 800-802. doi:10.1080/02640410410001675487
- Noakes, T. D., & Durandt, J. J. (2000). Physiological requirements of cricket. *Journal of Sports Sciences*, 18(12), 919-929. doi:10.1080/026404100446739
- Oliver, I. (1955). A spectrophotometric method for the determination of creative phosphokinase and myokinase. *Biochemical Journal*, 61(1), 116.
- Olivier, B., Taljaard, T., Burger, E., Brukner, P., Orchard, J., Gray, J., . . . McKinon, W. (2016). Which Extrinsic and Intrinsic Factors are Associated with Non-Contact Injuries in Adult Cricket Fast Bowlers? *Sports Medicine*, 46(1), 79-101. doi:10.1007/s40279-015-0383-y
- Orchard, J. W., Blanch, P., Paoloni, J., Kountouris, A., Sims, K., Orchard, J. J., & Brukner, P. (2015). Fast bowling match workloads over 5-26 days and risk of injury in the following month. *Journal of Science and Medicine in Sport*, 18(1), 26-30. doi:10.1016/j.jsams.2014.09.002
- Orchard, J. W., James, T., Kountouris, A., & Portus, M. (2010). Changes to injury profile (and recommended cricket injury definitions) based on the increased frequency of Twenty20 cricket matches. *Open Access Journal of Sports Medicine*, 1, 63-76.
- Orchard, J. W., James, T., Portus, M., Kountouris, A., & Dennis, R. (2009). Fast bowlers in cricket demonstrate up to 3- to 4-week delay between high workloads and increased risk of injury. *The American Journal of Sports Medicine*, 37(6), 1186-1192. doi:10.1177/0363546509332430

- Orchard, J. W., Ranson, C., Olivier, B., Dhillon, M., Gray, J., Langley, B., . . . Finch, C. F. (2016). International consensus statement on injury surveillance in cricket: a 2016 update. *British Journal of Sports Medicine*, *50*(20), 1245-1251. doi:10.1136/bjsports-2016-096125
- Oxendale, C. L., Twist, C., Daniels, M., & Highton, J. (2016). The relationship between match-play characteristics of elite rugby league and indirect markers of muscle damage. *International Journal of Sports Physiology and Performance*, *11*(4), 515-521. doi:10.1123/ijsp.2015-0406
- Padilla, S., Mujika, I., Orbananos, J., & Angulo, F. (2000). Exercise intensity during competition time trials in professional road cycling. *Medicine and Science in Sports and Exercise*, *32*(4), 850-856.
- Pallant, J. (2001). SPSS survival manual. A step by step guide to data analysis using SPSS for Windows (version 12), United Kingdom: Open University Press.
- Papacosta, E., & Nassis, G. P. (2011). Saliva as a tool for monitoring steroid, peptide and immune markers in sport and exercise science. *Journal of Science and Medicine in Sport*, *14*(5), 424-434. doi:<https://doi.org/10.1016/j.jsams.2011.03.004>
- Passelergue, P., & Lac, G. (1999). Saliva cortisol, testosterone and T/C ratio variations during a wrestling competition and during the post-competitive recovery period. *International Journal of Sports Medicine*, *20*(02), 109-113.
- Passelergue, P., Robert, A., & Lac, G. (1995). Salivary cortisol and testosterone variations during an official and a simulated weight-lifting competition. *International Journal of Sports Medicine*, *16*(5), 298-303. doi:10.1055/s-2007-973009

- Petersen, C. J., Portus, D. B., & Dawson, M. R. (2009). Quantifying positional movement patterns in Twenty20 cricket. *International Journal of Performance Analysis in Sport*, 9(2), 165-170.
- Petersen, C. J., Pyne, D., Dawson, B., Portus, M., & Kellett, A. (2010). Movement patterns in cricket vary by both position and game format. *Journal of Sports Sciences*, 28(1), 45-52. doi:10.1080/02640410903348665
- Petersen, C. J., Pyne, D., Portus, M., & Dawson, B. (2009). Validity and reliability of GPS units to monitor cricket-specific movement patterns. *International Journal of Sports Physiology and Performance*, 4(3), 381-393.
- Petersen, C. J., Pyne, D. B., Dawson, B. T., Kellett, A. D., & Portus, M. R. (2011). Comparison of training and game demands of national level cricketers. *Journal of Strength and Conditioning Research*, 25(5), 1306-1311. doi:10.1519/JSC.0b013e3181d82cfd
- Petersen, C. J., Pyne, D. B., Portus, M. J., & Dawson, B. (2008). Analysis of Twenty/20 Cricket performance during the 2008 Indian Premier League. *International Journal of Performance Analysis in Sport*, 8(3), 63-69.
- Petersen, C. J., Pyne, D. B., Portus, M. R., & Dawson, B. T. (2011). Comparison of player movement patterns between 1-day and test cricket. *Journal of Strength and Conditioning Research*, 25(5), 1368-1373. doi:10.1519/JSC.0b013e3181da7899
- Petersen, C. J., Pyne, D. B., Portus, M. R., Karppinen, S., & Dawson, B. (2009). Variability in movement patterns during One Day Internationals by a cricket fast bowler. *International Journal of Sports Physiology and Performance*, 4(2), 278-281.

- Phillips, E., Portus, M., Davids, K., & Renshaw, I. (2012). Performance accuracy and functional variability in elite and developing fast bowlers. *Journal of Science and Medicine in Sport, 15*(2), 182-188. doi:10.1016/j.jsams.2011.07.006
- Portus, M., Timms, S., Spratford, W., Morrison, N., & Crowther, R. (2010). *The utility of a bowling skills test to assist developing fast bowlers*. Paper presented at the 1 of 1-Conference of Science, Medicine & Coaching in Cricket 2010.
- Portus, M. R., Sinclair, P. J., Burke, S. T., Moore, D. J., & Farhart, P. J. (2000). Cricket fast bowling performance and technique and the influence of selected physical factors during an 8-over spell. *Journal of Sports Sciences, 18*(12), 999-1011. doi:10.1080/026404100446801
- Pyne, D. B., Duthie, G. M., Saunders, P. U., Petersen, C. A., & Portus, M. R. (2006). Anthropometric and strength correlates of fast bowling speed in junior and senior cricketers. *Journal of Strength and Conditioning Research, 20*(3), 620-626. doi:10.1519/R-18315.1
- Rampinini, E., Bosio, A., Ferraresi, I., Petruolo, A., Morelli, A., & Sassi, A. (2011). Match-related fatigue in soccer players. *Medicine and Science in Sports and Exercise, 43*(11), 2161-2170. doi:10.1249/MSS.0b013e31821e9c5c
- Rampinini, E., Coutts, A. J., Castagna, C., Sassi, R., & Impellizzeri, F. M. (2007). Variation in top level soccer match performance. *International Journal of Sports Medicine, 28*(12), 1018-1024. doi:10.1055/s-2007-965158
- Rebelo, A., Brito, J., Seabra, A., Oliveira, J., Drust, B., & Krstrup, P. (2012). A new tool to measure training load in soccer training and match play. *International Journal of Sports Medicine, 33*(4), 297-304. doi:10.1055/s-0031-1297952
- Ritchie, D., Hopkins, W. G., Buchheit, M., Cordy, J., & Bartlett, J. D. (2016). Quantification of training and competition load across a season in an elite

- Australian football club. *International Journal of Sports Physiology and Performance*, 11(4), 474-479. doi:10.1123/ijsp.2015-0294
- Ronglan, L. T., Raastad, T., & Borgesen, A. (2006). Neuromuscular fatigue and recovery in elite female handball players. *Scandinavian Journal of Medicine and Science in Sports*, 16(4), 267-273. doi:10.1111/j.1600-0838.2005.00474.x
- Rosalki, S. B. (1967). An improved procedure for serum creatine phosphokinase determination. *Journal of Laboratory and Clinical Medicine*, 69(4), 696-705.
- Rowell, L. B. (1993). *Human cardiovascular control*: Oxford University Press, USA.
- Rudkin, S. T., & O'Donoghue, P. G. (2008). Time-motion analysis of first-class cricket fielding. *Journal of Science and Medicine in Sport*, 11(6), 604-607. doi:10.1016/j.jsams.2007.08.004
- Russell, M., Sparkes, W., Northeast, J., Cook, C., Bracken, R., & Kilduff, L. (2016). Relationships between match activities and peak power output and Creatine Kinase responses to professional reserve team soccer match-play. *Human Movement Science*, 45, 96-101.
- Scott, A., Malone, J. J., Morgans, R., Burgess, D., Gregson, W., Morton, J. P., & Drust, B. (2016). The relationship between physical match performance and 48-h post-game creatine kinase concentrations in English Premier League soccer players. *International Journal of Sports Science and Coaching*, 11(6), 846-852. doi:doi:10.1177/1747954116676111
- Scott, B. R., Lockie, R. G., Knight, T. J., Clark, A. C., & Janse de Jonge, X. A. (2013). A comparison of methods to quantify the in-season training load of professional soccer players. *International Journal of Sports Physiology and Performance*, 8(2), 195-202.

- Scott, T. J., Black, C., Quinn, J., & Coutts, A. J. (2012). Validity and reliability of the session RPE method for quantifying training in Australian Football: A comparison of the CR10 and CR100 scales. *Journal of Strength and Conditioning Research*.
- Shephard, R. J., Hamm, L., Mertens, D. J., Beyene, J., & Kavanagh, T. (2002). Influence of initial fitness on the response to cardiac rehabilitation. *Medicine and Science in Sports and Exercise*, 34(5), S181.
- Slattery, K. M., Wallace, L. K., Bentley, D. J., & Coutts, A. J. (2012). Effect of training load on simulated team sport match performance. *Applied Physiology, Nutrition, and Metabolism*, 37(2), 315-322. doi:10.1139/h2012-001
- Slinde, F., Suber, C., Suber, L., Edwén, C. E., & Svantesson, U. (2008). Test-retest reliability of three different countermovement jumping tests. *Journal of Strength and Conditioning Research*, 22(2), 640-644. doi:10.1519/JSC.0b013e3181660475
- Smith, D. J. (2003). A framework for understanding the training process leading to elite performance. *Sports Medicine*, 33(15), 1103-1126.
- Spencer, M., Lawrence, S., Rechichi, C., Bishop, D., Dawson, B., & Goodman, C. (2004). Time–motion analysis of elite field hockey, with special reference to repeated-sprint activity. *Journal of Sports Sciences*, 22(9), 843-850.
- Stagno, K. M., Thatcher, R., & van Someren, K. A. (2007). A modified TRIMP to quantify the in-season training load of team sport players. *Journal of Sports Sciences*, 25(6), 629-634. doi:10.1080/02640410600811817
- Sterne, J. A., & Smith, G. D. (2001). Sifting the evidence—what's wrong with significance tests? *Physical Therapy*, 81(8), 1464-1469.

- Stretch, R. A., & Lambert, M. I. (1999). Heart rate response of young cricket fast bowlers while bowling a six-over spell. *South African Journal of Sports Medicine*, 6(1), 15-19.
- Stronach, B. J., Cronin, J. B., & Portus, M. R. (2014). Part 2: Mechanical and anthropometric factors of fast bowling for cricket, and implications for strength and conditioning. *Strength and Conditioning Journal*, 36(5), 53-60. doi:10.1519/Ssc.0000000000000095
- Stuelcken, M., Pyne, D., & Sinclair, P. (2007). Anthropometric characteristics of elite cricket fast bowlers. *Journal of Sports Sciences*, 25(14), 1587-1597. doi:10.1080/02640410701275185
- Taliep, M. S., Gray, J., Gibson, A. S., Calder, S., Lambert, M. I., & Noakes, T. D. (2003). The effects of a 12-over bowling spell on bowling accuracy and pace in cricket fast bowlers. *Journal of Human Movement Studies*, 45(3), 197-217.
- Talke, H., & Schubert, G. (1965). Enzymatische Harnstoffbestimmung in Blut und Serum im optischen Test nach Warburg. *Journal of Molecular Medicine*, 43(3), 174-175.
- Taylor, K., Chapman, D., Cronin, J., Newton, M., & Gill, N. (2012). Fatigue monitoring in high performance sport: a survey of current trends. *Journal of Australian Strength and Conditioning*, 20(1), 12-23.
- Thorlund, J. B., Aagaard, P., & Madsen, K. (2009). Rapid muscle force capacity changes after soccer match play. *International Journal of Sports Medicine*, 30(4), 273-278. doi:10.1055/s-0028-1104587
- Thorlund, J. B., Michalsik, L. B., Madsen, K., & Aagaard, P. (2008). Acute fatigue-induced changes in muscle mechanical properties and neuromuscular activity in elite handball players following a handball match. *Scandinavian Journal of*

Medicine and Science in Sports, 18(4), 462-472. doi:10.1111/j.1600-0838.2007.00710.x

Thorpe, R. T., Strudwick, A. J., Buchheit, M., Atkinson, G., Drust, B., & Gregson, W. (2015). Monitoring fatigue during the in-season competitive phase in elite soccer players. *International Journal of Sports Physiology and Performance*, 10(8), 958-964. doi:10.1123/ijsp.2015-0004

Torreño, N., Munguia-Izquierdo, D., Coutts, A., Sáez de Villarreal, E., Asian-Clemente, J., & Suarez-Arrones, L. (2016). Relationship between external and internal loads of professional soccer players during full matches in official games using global positioning systems and heart-rate technology. *International Journal of Sports Physiology and Performance*, 11(7), 940-946.

Twist, C., & Eston, R. (2005). The effects of exercise-induced muscle damage on maximal intensity intermittent exercise performance. *European Journal of Applied Physiology*, 94(5), 652-658. doi:10.1007/s00421-005-1357-9

Twist, C., & Highton, J. (2013). Monitoring fatigue and recovery in rugby league players. *International Journal of Sports Physiology and Performance*, 8(5), 467-474.

Urhausen, A., Gabriel, H., & Kindermann, W. (1995). Blood hormones as markers of training stress and overtraining. *Sports Medicine*, 20(4), 251-276.

Urhausen, A., & Kindermann, W. (2002). Diagnosis of overtraining. *Sports Medicine*, 32(2), 95-102.

van Schaik, P., & Weston, M. (2016). Magnitude-based inference and its application in user research. *International Journal of Human-Computer Studies*, 88, 38-50. doi:10.1016/j.ijhcs.2016.01.002

- Vickery, W. M., Dascombe, B. J., Baker, J. D., Higham, D. G., Spratford, W. A., & Duffield, R. (2014). Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. *Journal of Strength and Conditioning Research*, 28(6), 1697-1705. doi:10.1519/JSC.0000000000000285
- Vincent, H. K., & Vincent, K. R. (1997). The effect of training status on the serum creatine kinase response, soreness and muscle function following resistance exercise. *International Journal of Sports Medicine*, 18(6), 431-437. doi:10.1055/s-2007-972660
- Viru, A. A. (1987). Mobilisation of structural proteins during exercise. *Sports Medicine*, 4(2), 95-128.
- Viru, A. A., & Viru, M. (2001). *Biochemical monitoring of sport training: Human Kinetics*.
- Waldron, M., Twist, C., Highton, J., Worsfold, P., & Daniels, M. (2011). Movement and physiological match demands of elite rugby league using portable global positioning systems. *Journal of Sports Sciences*, 29(11), 1223-1230. doi:10.1080/02640414.2011.587445
- Weaving, D., Marshall, P., Earle, K., Nevill, A., & Abt, G. (2014). Combining internal- and external-training-load measures in professional rugby league. *International Journal of Sports Physiology and Performance*, 9(6), 905-912. doi:10.1123/ijsp.2013-0444
- Wehbe, G., Gabbett, T. J., Dwyer, D., McLellan, C., & Coad, S. (2015). Monitoring neuromuscular fatigue in team-sport athletes using a cycle-ergometer test. *International Journal of Sports Physiology and Performance*, 10(3), 292-297. doi:10.1123/ijsp.2014-0217

- Witte, T. H., & Wilson, A. M. (2005). Accuracy of WAAS-enabled GPS for the determination of position and speed over ground. *Journal of Biomechanics*, 38(8), 1717-1722. doi:10.1016/j.jbiomech.2004.07.028
- Woolmer, B., Noakes, T., & Moffett, H. (2009). *Bob Woolmer's art and science of cricket*: Struik Pub.
- World Medical, A. (2013). World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects. *Journal of the American Medical Association*, 310(20), 2191-2194. doi:10.1001/jama.2013.281053
- Young, W. B., Hepner, J., & Robbins, D. W. (2012). Movement demands in Australian rules football as indicators of muscle damage. *Journal of Strength and Conditioning Research*, 26(2), 492-496. doi:10.1519/JSC.0b013e318225a1c4
- Zar, J. H. (1999). *Biostatistical analysis*: Pearson Education India.

10. Appendices

Appendix A – Warm-up Protocol

Over a 10 metre course (Cones placed down at 0, 5 and 10 metres). Participants perform each exercise as instructed by the researcher. Diagram of the circuit can be seen below the exercises.

- 1) 4 sets*Light Jogging (= 8 times)
- 2) 2 sets*Side stepping (1 way there 1 way back = 4 times)
- 4) 2 sets*Heel Flicks & Up at front; on way back Outsides, Insides (5 on each leg; 10 in total = 4 times)
- 5) 2 sets*Skipping (with high arms = 4 times)
- 6) 2 sets*Jumping (Calf jumps up) every time at a cone (= 4 times)
- 7) 2 sets* Jockeying (Forwards and backwards up and down); 2 jockeys each way (= 4 times)
- 8) 2 sets*Adductors (Over gates up, Close gates back = 4 times)
- 9) 2 sets*Kicking through & Stamping (Up and Down = 4 times)
- 10) 2 set* Donkey Kicks (1/2 pace on way back = 4 times)
- 11) 2 set* Squats & Lunges (= 4 times)
- 12) 2 set* 5m sprint (walk on way back = 4 times)
- 13) 3 set* 10m sprint (walk on way back = 6 times)

Appendix B – Perceptual Well-being Questionnaire (adapted from Johnston et al., [2013] and McLean et al., [2010]).

	5	4	3	2	1	Score
Fatigue	Very fresh	Fresh	Normal	More tired than normal	Always tired	
Sleep Quality	Very restful	Good	Difficulty falling asleep	Restless sleep	Insomnia	
General Muscle Soreness	Feeling great	Feeling good	Normal	Increase in soreness/tightness	Very sore	
Stress Levels	Very relaxed	Relaxed	Normal	Feeling stressed	Highly stressed	
Mood	Very positive mood	A generally good mood	Less interested in others and/or activities than usual	Snappiness at team-mates, family and co-workers	Highly annoyed/irritable/down	

Appendix C – Borgs Category Ratio 10 (CR10) Scale of Perceived Exertion. As modified by Foster et al., (2001).

0	Rest
1	Very, Very Easy
2	Easy
3	Moderate
4	Somewhat Hard
5	Hard
6	
7	Very Hard
8	
9	
10	Maximal