MODELING THE RELATIONSHIP BETWEEN WORKLOAD AND NON-CONTACT INJURIES IN AMERICAN COLLEGE FOOTBALL PLAYERS

By

William Pastors Burghardt

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PUBLIC ABSTRACT

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Physical activity can promote positive physical changes which, when performed repeatedly, can result in improvements to sport performance. However, activity that is too intense or too frequent may result in potential injury. Reducing injury occurrences and severity has shown to be critical for competitive success. In college football, injury rates have been reported to be 7.14 per 1,000 athlete exposures (AEs), with 35% occurring from a non-contact or overuse cause. A potential contributor to these injuries may be the length and intensity of sport activities that athletes experience following periods of time-off. Another contributor could be the rate that athletes experience this increased activity. In response, sport practitioners have begun measuring athlete activity during training and competition. Research has shown relationships between the amount of activity (workload), the rate of activity exposure, and ensuing non-contact injury. However, these studies have drawn criticism for how these relationships were assessed and the lack of an associated path between activity and injury. In response, the purposes of this dissertation were to 1) utilize modern techniques to assess the relationships among injuries, activity, and rate of activity increase at a particular point of the season between two different teams, 2) determine the non-contact injury rates for each phase of the calendar year and assess the relationship of injury occurrence to activity and activity rates within one team, and 3) to evaluate if inflammation may be a key component on the path between activity and non-contact injuries.

Our first study measured workload, workload ratio, and non-contact injuries from two football teams (120 athletes) across two seasons. Both teams observed 44 total non-contact injuries, however the difference in reported injuries which resulted in time-loss from sport (Team 1: 6; Team 2: 17) led us to question if teams used different criteria for removing an athlete from team activities. Teams had different workload and workload ratios in each phase of the year. Our calculations demonstrated that workload and workload ratios were associated with injuries. However increased activity was associated with lower chance of injury, and workload ratios were only associated with a higher chance of injury to a point. These relationships were consistent with our second study, which examined these measures across nearly three years of data from one team (n = 88). The pre-season practice phase was the largest in both workload and time-loss non-contact injury rate (4.70 AEs), however, winter conditioning (2.84 AEs), spring practice (2.64 AEs), and summer conditioning phases (1.42 AEs) had injury rates higher than in-season (1.20 AEs). This suggests the need to monitor these other phases of training. Finally, we assessed C-reactive protein in 19 football players during a pre-season and in-season period to determine if workload and workload ratios led to increased inflammation (CRP), which led to non-contact injury. However, our study showed that CRP did not vary across time and was poorly related to any difference in activity from week to week. However, the observance of only one time-loss non-contact injury limited our findings.

Overall, our studies highlight the strengths and weaknesses of the current workload and workload ratio research. Further research should be conducted across multiple teams and years in order to observe enough non-contact injuries to permit the use of certain statistical tools that would be more useful to practitioners and coaches. In addition, further research should continue to see if there is a path between seek to find mediating pathways between activity and injury.

ABSTRACT

MODELING THE RELATIONSHIP BETWEEN WORKLOAD AND NON-CONTACT INJURIES IN AMERICAN COLLEGE FOOTBALL PLAYERS

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Physical activity is widely used in sport to promote positive physiological adaptations which, when performed systematically over a sustained period, can elicit improvements in sport performance. However, activity sessions that are too intense or occur too frequently may result in injury. Injury mitigation has shown to be critical for competitive success. In college football, injury rates of 7.14 events per 1,000 athlete exposures (AEs) have been observed, with 35% occurring from a non-contact or overuse mechanism. Contributing to these injuries may be the rate at which athletes are exposed to activity. In response, sport practitioners have begun measuring athlete activity (workload) during training and competition. Research has shown associations among the amount of workload, the rate of workload exposure, and subsequent non-contact injury. However, these studies have drawn criticism for both the statistical methods used and the absence of a supporting injury framework. In response, the purposes of this dissertation were to 1) utilize modern statistical practices to assess the relationships among injuries, workload, and workload ratios between two different teams, 2) determine the non-contact injury rates for each phase of the calendar year and assess the relationship to workload and workload ratios within the same team, and 3) to evaluate if systemic inflammation may be a mediator between workload and non-contact injury events.

The first study measured workload, workload rate, and non-contact injuries from two football teams (120 athletes) across two seasons. Both teams observed 44 non-contact injuries, however, the discrepancy between injuries resulting in time-loss from participation (Team 1: 6;

Team 2: 17) led us to question if team medical personnel utilized different criteria for sport modification/removal. Workload and workload ratios in each phase differed significantly by team. Generalized estimating equation (GEE) models were significantly associated with injuries (EWMA: Wald $\chi^2 = 42.40$, $p < .005$; ACWR: Wald $\chi^2 = 32.49$, $p < .005$), however, increased weekly loads were associated with lower injury probability (Odds Ratio: 0.15, $p < .005$), and workload ratios demonstrated an inverted-U relationship to injury. Our second study examined these measures for one team (n = 88) from 2017 thru 2019. The pre-season practice phase was the largest in both volume and time-loss non-contact injury rate (4.70 AEs), however, winter conditioning (2.84 AEs), spring practice (2.64 AEs), and summer conditioning phases (1.42 AEs) had injury rates higher than in-season (1.20 AEs), thus suggesting the need to monitor other phases of training in addition to the pre-season and in-season phases. GEE models demonstrated similar results to Study 1. Finally, a 12-week analysis of salivary C-reactive protein concentrations (CRP) was conducted to investigate the association of systemic inflammation to workload rates and non-contact injury. CRP concentrations in football players (n = 19) over a pre-season and in-season did not vary across time and was poorly correlated to weekly change in workload (r = 0.15) and workload ratios (EWMA: r = -0.11; ACWR: r = -0.07). However, the observance of only one time-loss non-contact injury limited our conclusions. Overall, our studies highlight the strengths and weaknesses of the current workload and workload ratio research. Further research should be conducted across multiple teams and years to observe enough non-contact injury events to permit the use of statistical methods that yield greater generalizability and utility to practitioners and coaches. In addition, further research should seek to find mediating pathways between activity and injury.

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I would like to dedicate this dissertation to my wife Alaina and my children, Annabelle, Liam, and Emelia. To my children, you are my motivations every day to be the best version of myself I can be. I am honored to be your dad and I hope I can be an example of how humility, passion, and perseverance can help you achieve your dreams. I know the process of obtaining this degree and writing this dissertation felt like an eternity to you, it did to me as well. I cannot wait to play, color, and cuddle with you all again. I love each one of you with greater passion than I could ever convey. To my wife, I can never fully express my love and gratitude for everything you have done, and sacrificed, so I could chase this dream. Absolutely none of this would have been possible without you. Thank you, I love you, and I am proud to be your husband.

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KEY TO SYMBOLS AND ABBREVIATIONS

ACWR	Acute:chronic Workload Ratio
AEs	1,000 Athlete Exposures
AU	Arbitrary Units
ANOVA	Analysis of Variance
APR	Acute-Phase Response
CI	Confidence Intervals
CR-10	Borg scale of rating of perceived exertion from 0-10
CRP	C-Reactive Protein
η^2	Partial Eta-squared statistic
EWMA	Exponentially Weighted Moving Average
g	gravitational force
GEE	Generalized Estimating Equation
GPS	Global Positioning System
HEs	1,000 Hour Exposures
hGH	Human Growth Hormone
HR	Heart Rate
HSR	High Speed Running
IGF-1	Insulin-like Growth Factor 1
IL-1	Interleukin-1
IL-6	Interleukin-6
IRR	Incidence Rate Ratio

km/h	kilometers per hour
mg/L	milligrams per Liter
mph	miles per hour
NCAA	National Collegiate Athletic Association
OR	Odds Ratio
PL	Player Load
P-R	Precision-Recall curve
QIC	Quasilikelihood under the independence model criterion
r	Pearson correlation
ROC	Receiver Operating Characteristic
RR	Relative Risk
SE	Huber-White Standard Errors
SHRZS	Summated Heart Rate Zone Score
SOCS	Suppressors of Cytokine Signaling family
sRPE	Session Rating of Perceived Exertion
TRIMP	Training Impulse
VO_2	Aerobic capacity
χ^2	Wald chi-square statistic

CHAPTER 1

INTRODUCTION

Physical activity, injuries, and college football

When planned correctly, physical training sessions can induce positive physiological adaptations (11, 23, 41, 191). Athlete physiological responses are related to the mode, intensity, and duration of the training stimulus (211). Though a single exercise session generates a transient acute adaptive response, repeated bouts of such stimuli are necessary to elicit desirable and lasting physiological adaptations(211). However, should these stimuli be too intense or too frequent, then maladaptive processes, including injury, may occur(87-89). It is the responsibility of the coaches, practitioners (i.e., strength & conditioning coaches, athletic trainers, physical therapists, etc.), and athletes to appropriately monitor the training environment to ensure optimal performance and injury mitigation (69, 87, 123).

Approximately 29,000 football players compete at the NCAA Division 1 level each year (5). As one would anticipate, injuries are common in elite-level American football (football) (133, 137). The mitigation of injury occurrence is vital in team sports for both athlete health and overall team success(69, 87, 123). Recent injury rates at the NCAA Division 1 level were observed to be 7.14 incidences per 1,000 athlete exposures (AE's) (133). Injury rates for competitions and practices are 34.06 and 4.63 respectively(133). Because the ratio of practices to games is 4- or 5-to-1, a greater percentage of injuries are sustained during practice (40.5% vs 59.5% respectively) (133). Furthermore, pre-season practices had higher rates of injury (8.74) than practices during the regular season (2.82) and postseason (2.52) (133). Approximately 35% of total injuries sustained during collegiate football practice occur via a non-contact (30.3%) or

overuse/chronic (4.8%) mechanism(133). Recent research in football(188, 189) and other sports(68, 81, 102, 114-116, 150, 151, 156, 169, 186, 204, 219) has suggested that a contributing variable to these injuries may be the rate at which athletes increase their conditioning and practice exposure (workload).

Measurements of physical activity

Several methods have been used to quantify workout, such as Session Rating of Perceived Exertion (sRPE)(88) and heart rate-based training impulse (TRIMP) (10). To reduce injury risk and optimize individual performance, teams started tracking athlete workloads using novel wearable devices comprised of global positioning systems (GPS) with built-in accelerometers and gyroscopes. These devices have been used as tools to quantify movement demands in numerous studies including team sports such as rugby(59, 68, 115, 116), soccer(83, 125, 149, 150), and Australian Rules football(68, 167-169, 204). Research has shown associations with non-contact and overuse injury occurrence when athletes increase their recent (acute) activity at rates greater than 1.5 to 2.0 times their past (chronic) exposure; this is frequently termed the traditional acute:chronic workload ratio (ACWR) (65, 114, 156, 168, 169, 188). This ratio has been calculated using various mathematical approaches(102, 155). The two most common are the original 7-day acute to 28-day chronic method which utilizes rolling averages, and the 7-day acute to 21-day chronic method with exponentially weighted moving averages (EWMA) (102, 155). Researchers believe the EWMA approach is preferable, since it takes the ability of fitness and fatigue effects to decay over time into account by assigning a decreasing weight to compensate for the latency effects of load(228). In college football, the 7:21-day coupled ACWR calculated using the EWMA method with a 3-day injury lag period

demonstrated the highest correlation to injury ($R^2 = 0.54$) during the pre-season and in-season periods(188). However, it remains unclear if this model is further generalizable to the entire training calendar. In addition, authors have recently been skeptical of conclusions drawn from the data when researchers discretize the ACWR instead of examining it as a continuous variable(36, 163, 216). Thus, EWMA is a promising approach to quantifying workload but needs further investigation.

Current NCAA policies indicate a strong probability that athletes experience at least a 2.5-fold increase in workload when they begin pre-season practice(6). The pre-season period for college football occurs in August and is approximately four weeks in length(6). Prior to this period, college football players spend an additional eight weeks of weight training and conditioning for their sport. The NCAA limits all weight training and conditioning activities to a combined eight hours per week during this period. The pre-season period in August allows for 20 hours per week of practice and weight training sessions. The 20 hours per week of activity allowed in August is 2.5-times greater than the allotted summer training time. Based on the research discussed prior, it may be suggested that this transition could be an area of potential increased injury risk for athletes.

Physiological responses to physical activity

During periods of increased workloads, athletes will experience transient muscle tissue damage(78). This damage results in an acute inflammatory response including the release of cytokines(40, 43, 46, 66, 85, 180). These cytokines aid in the removal of damaged cells(40). C-reactive protein (CRP) is a cytokine which has shown increased levels in circulating blood plasma after moderate and vigorous physical activity(67, 84). Although inflammation is

essential for the repair and adaptation processes to occur(40), elevated levels of this biomarker for prolonged periods affect an athlete's ability to repair this tissue(40, 85), thereby increasing their risk of sustaining an injury(45, 87). Determining associations among workload, CRP levels, and subsequent injury provides practitioners with greater understanding of the underlying mechanisms predisposing athletes to injury under periods of increased training or reduced recovery.

In response, the overall purposes of this dissertation were to 1) utilize modern statistical practices to assess the relationship between injuries, workload, and workload ratios between two different teams, 2) determine the non-contact injury rates for each phase of the calendar year and assess the relationship to workload and workload ratios, and 3) to evaluate if systemic inflammation may be a mediator between workload and non-contact injury events. In line with the overall purpose of this dissertation, the proposed following specific aims and hypotheses are addressed in three separate studies.

SPECIFIC OBJECTIVES AND HYPOTHESES

Objective 1: To compare the relationship between workloads, workload ratios, phases of training, and non-contact injury occurrence across two Division 1 college football teams.

- Hypothesis 1a: Both teams will have similar workloads, workload ratios, and injury occurrences; but the values of these measures will be significantly difference across time.
- Hypothesis 1b: The EWMA workload ratio calculation will be more associated with non-contact injury risk than the ACWR calculation.

Objective 2: To assess the relationship between workload ratios and non-contact injury risk in each phase of American football training and participation utilizing a multi-year approach, with calculations for exponentially weighted moving average (EWMA) and traditional acute:chronic (ACWR) workload models.

- Hypothesis 2a: High EWMA and ACWR values will be significantly associated with increased non-contact injury risk for all time points during the training and competition cycle.
- Hypothesis 2b: EWMA will possess greater association with injury-risk than traditional A:C model and thereby be a better model for future endeavors.

Objective 3: To evaluate if systemic inflammation, measured via weekly C-reactive protein (CRP) samples, in American college football players during their training and sport participation are associated with increased non-contact injury risk.

- Hypothesis 3a: Athletes will experience significant increases in their CRP protein levels during the pre-season practice period.
- Hypothesis 3b: There will be a positive association between CRP levels and non-contact injury risk throughout the preseason and in-season periods.

The results from these studies will help inform practitioners and coaches of proper program development to minimize non-contact injury occurrence, thereby maximizing positive training adaptations and performance. This dissertation is separated into chapters. Chapter 2 provides a review of the literature with regards to the wearable devices in sporting environments and the relationship to injury. Chapter 3 addresses Objective 1 (Multi-team workload-injury association), Chapter 4 addresses Objective 2 (Multi-year workload-injury association), and Chapter 5 addresses Objective 3 (CRP association with injury). To conclude, Chapter 6 summarizes the findings within this dissertation and provides avenues for further study.

CHAPTER 2

LITERATURE REVIEW

Introduction

Athletes and coaches are constantly striving to improve performance by promoting positive physiological adaptations, and reducing the incidence of injuries, to achieve success(69, 87, 88, 123). The proper planning of training sessions is vital to achieve these goals(11, 23, 41, 87, 88, 191). These physiological adaptations are relative to the mode, intensity, and duration of the training stimuli(211). However, too intense, or frequent training stimuli may lead to maladaptive processes and the potential for injury(87-89). It is the responsibility of the coaches, practitioners(i.e., strength & conditioning coaches, athletic trainers, physical therapists, etc.), and athletes to appropriately monitor the training environment to ensure optimal performance and injury mitigation(69, 87, 123).

With the development of new technologies, coaches, athletes, and practitioners have been able to glean more data from training and competition sessions in order minimize these maladaptive responses. Mathematical modeling of these data has suggested that rapid increases in activity are related to future injury(65, 156, 168, 169, 188). However, the statistical analyses supporting these mathematical models have recently been called to question(36, 163, 216). Furthermore, there are few studies in American football and none utilizing the statistical methods suggested by the critics of past research. Therefore, a need exists to determine the association of these mathematical models to subsequent injury risk in American football players, as well as the supporting framework through which to assess this relationship. This review examines the strengths & limitations of previously implemented strategies to measure workload. Responses to

training stimuli are also reviewed. Further, injuries and injury frameworks are reviewed with respect to football and training. Lastly, gaps in current research are highlighted, including the analysis of C-reactive protein (CRP) levels as precursor to injury, as well as the utilization of larger, multi-year data sets to produce generalizable findings for elite college football.

Injury Framework

Several frameworks for injuries in sports have recently been proposed(9, 21, 129, 162, 230). Bahr and Krosshaug(9) proposed a framework where internal risk factors predispose an athlete to injury. These factors included age, sex, body composition, previous injury, physical fitness, anatomy, skill level, and psychological factors. The predisposed athlete becomes a susceptible athlete after exposure to external risk factors such as sport coaching, rules, protective equipment, performance equipment, and environment. Susceptible athletes then experience an inciting event such as playing situation or behavior from the player or an opponent behavior. This inciting event leads to injury. This model provides a precise description of the inciting event component of the injury causal pathway to guide future research(9).

Though having a better understanding of the inciting event is important, the internal and external risk factors preceding this event are not necessarily linear(162). Meeuwisse and colleagues(162) contend that injury does not always occur when certain risk factors are experienced, nor does injury permanently remove an athlete from participation. Therefore, a linear approach which contains a start and end point does not reflect the reality of sport(162). These authors proposed a recursive model where the susceptible athlete either experiences an inciting event and becomes injured or does not become injured. Both pathways may lead to adaptations; however, the injured pathway has a recovery component prior to potential

adaptations. The injured pathway may also lead to no recovery, where athletes are subsequently removed from participation and the recursive model. This model emphasizes that adaptations occur in sport and that these adaptations may alter the risk of injury in a dynamic, recursive manner(162).

The model by Meeuwisse and colleagues allows for a continual flow from participation to adaptation or injury and then back to participation(162). However, this model does not address tissue damage, mechanical failure, or the concepts of load tolerance and load application(129). All these factors contribute to the stress-, strain-, and overuse-related injuries prevalent in football(78, 133). Therefore, it is important to use an injury framework that accounts for these factors when investigating the association between load and fatigue-related injuries. Perhaps the framework which has the greatest applicability to the studies presented herein is the novel framework proposed by Kalkhoven et al. (Figure 1) (129). This framework adds causal pathway to the frameworks discussed previously to provide greater detail to the interplay of an individual's physiology, mechanics, and tissue loading. As a result, it is well-suited for stress-, strain-, and overuse-related injuries that are being observed in this thesis.

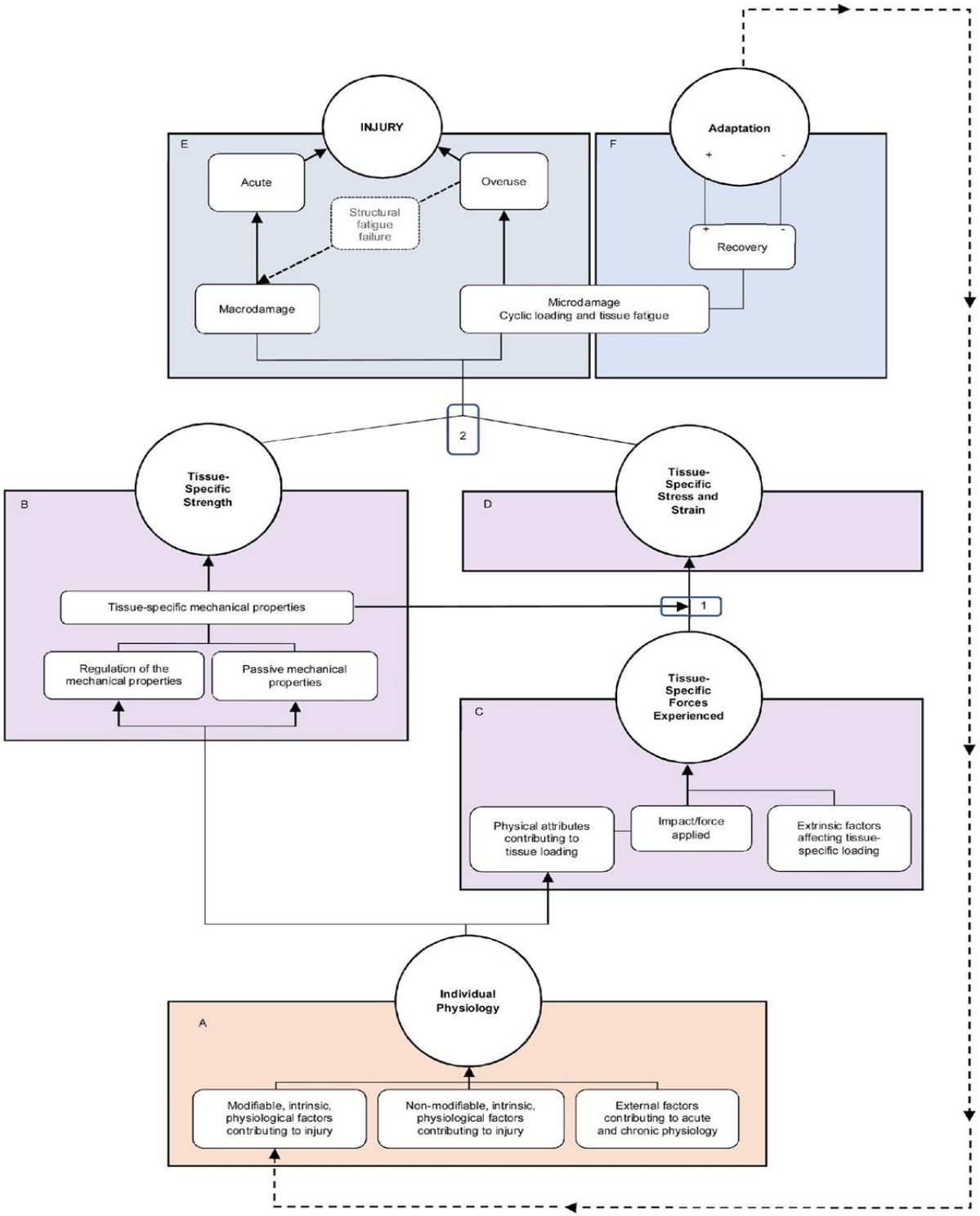

Figure 1.1. A detailed framework for stress-related, strain-related, and overuse injury, Reprinted from "A conceptual model and detailed framework for stress-related, strain-related, and overuse athletic injury", by Kalkhoven JT et al., Journal of Science and Medicine in Sport, In Press, Copyright(2020) by Elsevier B.V., https://doi.org/10.1016/j.jsams.2020.02.002.

Their framework has several subcomponents which inevitably result in either injury or adaptation. The first component is the individual's physiology. This is comprised of physiological factors which are either modifiable, non-modifiable, or external factors affecting that physiology. Some modifiable risk factors which fit into this category include, but are not limited to, body composition(172), bone mineral content(171), muscle structure(206), optimal muscle length(32), and tendon structure(23). Non-modifiable factors include age(160), gender(160), height(215), previous injury(153, 185, 215), blood type(130), and skeletal structure(202). The external factors related to this category include external training workload(160, 185, 215), training methods(44, 176), nutrition(171), warm-up(18), cool down(18), stretching(18), sleep(91, 92), and medications(171).

Components two and three extend from component one. Component two is tissue-specific strength(129). This includes both regulated and passive mechanical properties. These mechanical properties are individualized to each athlete. Alterations to the physiology of these tissues can directly affect the mechanical properties of the tissue, which ultimately modifies the tissue's resiliency to injury(129). The regulated properties include muscle hypertrophy, strength, and stiffness. Tendons and bones do not normally alter their mechanical properties; however, they do undergo chronic physiological adaptations(129). Physiological risk factors that can lead to injury include acute fatigue(75), acute glycogen depletion(97), and muscle acidification(75).

Component three addresses the tissue-specific forces experienced during the activity. This component is comprised of the physical attributes impacting tissue load, the impact or force applied to the tissue, as well as the extrinsic risk factors affecting the tissue-specific loading(129). Physical attributes which are captured in this component include speed, strength, neuromuscular control, balance, muscle agonist-antagonist relationship, etc. Impact and force

components can stem from ground reaction forces, forces received from contact with another person and contact with equipment. Extrinsic factors include playing surfaces, shoes, and other factors external to the athlete. Together, components two and three contribute to the fourth component.

The fourth component in the novel framework is tissue specific stress and strain(129). This framework addresses biological tissue through the lens of material science. This implies that the failure of tissue results when excessive stress or strain exceeds the tissue's ability to absorb such forces(78, 98, 179). Tissue failures can be the result of a large singular event or repetitive, lower threshold events(78, 98, 179).

It should be noted that these events do not necessarily have to lead to diagnosed injuries. If tissues are not compromised to structural failure, then positive physiological and mechanical adaptations such as muscle hypertrophy(19, 52, 191-194), increased muscle strength(19, 52, 191-194), tendon adaptations(23), and bone mineral density improvements(41, 96, 128, 170) all may occur as the result of stressors being placed on the tissue. However, in bringing this framework back to the fitness-fatigue model introduced earlier, without proper rest and recovery these tissues can be damaged to the point of an injury occurring(37, 94, 233). The authors complete their framework with these resulting injuries or adaptations impacting the first component of an individual's physiology.

The framework by Kalkhoven and colleagues(129) will provide the lens through which the data collected will be viewed for the studies presented in this thesis. It is expected that sudden increases in external workload will result in tissue damage(37, 78, 233). This tissue damage will cause an increase in the inflammatory biomarker CRP. The damaged tissue and inflammation will lead to greater risk of injury for athletes. As noted previously, there are very

few studies which utilize college football athletes as the principal population group. Therefore, this thesis also aims to develop models of external workload and injury with larger data sets, as well as to assess the relationship of these models utilizing optimal statistical instruments.

Fitness-Fatigue Model

Designing and implementing training sessions that promote positive physiological adaptations is a key objective for coaches and practitioners. However, as noted previously, it is important that the training stimulus does not exceed the mechanical properties and adaptation processes of the systems involved(129). Indeed, athletes will experience both fitness and fatigue effects as a result of these training sessions(11). To model performance with both the fitness and fatigue effects from training, Banister et al. proposed the fitness-fatigue model(11). The positive fitness effects include increases in muscle size, strength, recruitment patterns, oxygen consumption efficiency, mitochondrial density, blood supply, etc. (45). These effects work to increase subsequent performance. The fatigue effects, by contrast, are detriments to performance resulting from a depletion in energy substrate availability(56, 105, 205), or from increases in inflammation leading to soreness and edema(68, 191). The severity and duration of these effects depends on the intensity of the training stimulus(11, 88).

The model by Banister and colleagues also suggests that the intensity of one's training yields varying physiological adaptations(11). A training session with a high intensity and duration will cause greater levels of fatigue than a session of lighter intensity or shorter duration. However, according to this model, the benefit from these sessions, termed "supercompensation", will be greater over time. The term given to the decline in performance and subsequent increase in fatigue is termed "short-term overreaching" or "functional overreaching"(87, 89, 136). In

order for short-term overreaching to turn into supercompensation, a period of recovery is required(87, 89). If continued high intensity or prolonged training occurs while an athlete is still in a fatigued state, then the current session will simply compound the fatigue to a point where an athlete may not be able to adapt(11). Repeated high intensity sessions will continue to drive performance down and fatigue up. This can lead to overtraining syndrome(15, 89, 136).

Overtraining syndrome has a multitude of symptoms both physical and mental(136). Physical symptoms include heavy, sore, and stiff muscles, fatigue, hypertension, tachycardia or bradycardia, and weight loss(136). Mental symptoms include depression, irritability, insomnia, lack of concentration, and anxiety(136). Overtraining syndrome generally requires a sustained period of training where an athlete is unable to recover physically or mentally(89, 136). In previous research, athletes were generally able to experience short-term training intensities of 2-to-3 times their normal volumes for periods of 1-3 weeks without the onset of overtraining syndrome(90, 205). However, overuse and non-contact injuries may still occur without an athlete being diagnosed with overtraining syndrome (65, 125, 145, 156, 188).

Injuries in Football

Football is a sport involving a large number of contacts(220, 221). Contacts can occur between a player and a surface, equipment, or other players(133). Injuries which occur in the absence of these mechanisms are termed non-contact and overuse injuries(133). Strains (51.8%) and sprains (21.7%) comprise most of the noncontact and overuse injuries experienced in college football(133). Injuries from non-contact mechanisms in football make up 14.3% of competition injuries(133). This mechanism, however, comprises 30.4% of all injuries during practice(133). Overuse injuries stem from recurring microtrauma(224). This microtrauma causes degradation

in local tissue and generally occurs during sudden changes in mode or increases in intensity or duration of training(136, 140, 224). Overuse injuries, although lower in occurrence relative to non-contact injuries, occur in practice at 5-times the frequency compared to competitions (5.2% vs 1.1% respectively). While injuries have been classified as non-contact(49, 65, 81, 102, 156, 157, 168, 169, 188) or overuse (125, 145, 207, 219) in previous research, including the NCAA Injury Surveillance Program(133), both can occur as a result of fatigue(129). This is supported by Wilder and colleagues, who suggest that on the systemic level, sudden spikes in training load without proper recovery may lead to overtraining syndrome(224).

Fatigue may also play a role in non-contact muscle strain occurrence. As noted above, muscle strains comprise a large percentage of injuries sustained during football practice. Muscle strains frequently occur as a result of the muscle fibers undergoing an eccentric contraction while being forcefully lengthened(147). In rabbits, fatigued and non-fatigued muscles demonstrated equal failure points in terms of length; however, the fatigued muscles absorbed less energy than their non-fatigued controls(147). The non-fatigued muscles, Mair and colleagues concluded, were able to resist lengthening better than the fatigued muscles(147). Studies in the sporting population have observed a greater occurrence of muscle strains at the end of practices and competitions which give support to the laboratory results seen by Mair and colleagues(34, 80, 232). Given the mechanism by which many muscle strains occur, a fatigued state can increase an athlete's susceptibility to sustaining these injuries.

The repetitive bouts of high force output which induce fatigue in football players can also damage the other components of motor units besides the muscle fibers themselves. Barbe and colleagues(12) examined exposure-dependent changes in musculoskeletal and neurological tissue in rats after repeated bouts of activity at varying intensities. They found that high repetitions

performed at high forces induced the greatest tissue degenerative changes in not only muscle fibers, but tendons, bones, and nerves, even after six weeks of training. The authors concluded that beneficial adaptation could occur with prolonged performance if the number of repetitions is limited, and sufficient time is provided for the tissues to adaptively remodel. Otherwise, tissue inflammation and microdamage can be expected. These laboratory findings support the recommendation from Kerr and colleagues(133) that a phase-in approach should be utilized in football to provide adequate recovery. Transferring this laboratory information to the football sporting context, however, remains challenging. Besides the intrinsic drive of elite athletes to push their training regardless of the presence of pain, injury, or other health issues(47), there is a void in the literature as to the definition of appropriate offseason activity values are in college football. Also missing from the literature is what happens when the rate of activity increases as teams transition from off-season to pre-season practice. As a result, more research is needed to determine what constitutes high repetition counts and adequate recovery.

C-Reactive Protein

The muscle protein synthesis and degradation systems, which are affected by the presence or absence of physical activity, are regulated by a coordinated network of signaling pathways which are upregulated or downregulated by hormones and cytokines(54). Intense physical activity, including football participation, can have both anabolic and catabolic effects on muscle protein synthesis(79). Post-exercise anabolic signals are stimulated by insulin, insulin-like growth factor-1 (IGF-1), growth hormone (hGH), and other androgens(54). These signals have several positive down-stream effects, including muscle hypertrophy, which allow for tissue growth, adaptation, and increased performance(1, 35).

Moderate to vigorous physical activity incites transient muscle damage(78). Damaged muscle cells undergo catabolic processes as a result of the immune system's acute-phase response (APR) (131). The APR includes a multifaceted mediator cascade which seeks to minimize the extent of myofiber damage and subsequently promote recovery(131). The APR also includes an upregulation and expression of proinflammatory cytokines. These cytokines include interleukin-1 (IL-1) and interleukin-6 (IL-6). IL-1 increases the production of IL-6, which in turn increases the production of another proinflammatory cytokine, C-reactive protein (CRP) (117).

CRP is produced primarily in the liver and is able to bind to a wide variety of ligands including the phospholipids phosphatidylcholine and phosphorethanolamine. These ligands comprise large portions of the cell membranes including myofibers(22). CRP, however, can only bind to the phosphocholine head of these ligands when the cells are damaged(22). The binding of CRP to these damaged cells aids in their clearance, thereby allowing healthy new cells to take their place and restore optimal tissue function(237). Normal CRP concentration levels in healthy adults has been reported to range between 0.8 mg/L and 3.0 mg/L (197). However, CRP concentration levels have been shown to increase 1,000-fold over 1-3 days after tissue damage or the onset of inflammation (93, 159). Sustained levels of CRP greater than 3 mg/L have also been correlated with cardiovascular disease, frailty, morbidity, and mortality(2, 187). As stated previously, moderate to vigorous physical activity has been shown to cause increases in CRP concentration post-activity (67, 84). Given that the half-life of CRP is approximately 19 hours (210), and that circulating CRP concentrations from physical activity can be present from 1 to 4 days post-activity, utilizing CRP as a marker for chronic inflammation is possible(40). It should be noted that regular exercise is associated with systemic anti-inflammatory effects (86).

However, intense exercise, especially when it is combined with reduced recovery periods, can yield chronic inflammation (40). This inflammation can occur locally in the muscle tissue as well as the entire body. Intense exercise can promote this chronic inflammation through elevated IL-6(40, 181). Prolonged elevation of IL-6 promotes a negative feedback loop on the suppressors of cytokine signaling (SOCS) family. This negative feedback loop decreases the signaling linked with human growth hormone (hGH) and insulin-like growth factor-1 (IGF-1). This reduced signaling inhibits the repair and positive adaptation mechanisms within the damaged tissue(40, 85, 103). Therefore, the imbalance of fitness and fatigue may predispose athletes to greater chances of injury(45, 87).

Although a key indicator of inflammation, CRP has not been studied extensively in elite athletics, and results from the studies that have been performed are mixed. For instance, elite futsal players demonstrated a 1.6-fold increase in CRP levels after matches (40, 64). In elite rugby union players, acute heavy impacts and high competitive workloads, similar to what can be expected in football, were significantly correlated with muscle damage (70). However, not only was this damage demonstrated via creatine kinase levels and not CRP, but these levels were also uncorrelated with injuries(70). It should be noted that this study only had 3 samples taken per athlete over the course of the entire season. This may have affected the ability to detect smaller fluctuations from week to week. To the author's knowledge, there has not been a study performed in American football assessing CRP levels over the course of a season. It is possible that the increased and condensed training that takes place during the pre-season practice period may result in an increase in circulating CRP levels. The repetitive skeletal muscle damage associated with this time period as well as in-season sport participation, may promote the negative feedback loop on SOC. This systemically inflamed state may promote a great risk of

non-contact injury. As a result, weekly assessment of CRP concentrations in football players during these periods of training and sport participation is warranted. Should associations be found between workload, CRP levels, and subsequent injury in elite football players, we could then begin to develop a temporal relationship between these variables and assess future research to intervene within this injury framework.

Quantification of Workload

Although it intuitively makes sense that prolonged, intense training sessions without adequate rest and recovery can incite maladaptive responses in athletes, and that these responses can predispose athletes to injury, there is a need to quantify these sessions to effectively manage training load. Various methods of been developed to quantify these loads. These methods can be categorized as internal or external(27). Common measures of internal workload in the sporting context include heart rate(3, 26, 110, 161, 200, 214) and ratings of perceived exertion (15, 49, 58, 65, 108, 149, 151, 161, 200, 204, 214). Ratings of perceived exertion are also a considered subjective measure because it is reported by the athlete, whereas heart rate is measured via monitors and is therefore considered an objective measure of workload(27). External measures are also objective and include both GPS-derived parameters (i.e. distance and velocity) and accelerometer-derived parameters (i.e. jumps, throws, contacts, and cumulative load)(27). Each of these workload quantification techniques has its benefits and limitations and will be discussed further.

Heart Rate-Based Quantification of Workload

Previous research has shown that heart rate (HR) increases linearly with increased oxygen consumption at working tissues (VO_2) during steady-state, submaximal exercise(7). This has led to the development of models to quantify exercise training demand based on heart rate(10, 76, 144). Banister and colleagues(10) provided a method to determine the intensity of training sessions based on training session duration and the heart rate response of the athlete during that session. Together these variables were called the training impulse (TRIMP). They suggested that this method could be a potential measure of physical stress because it is based on the elevation of the heart rate in response to the demands of exercise. The formula for TRIMP is:

$$w(t) = D\ x\ \Delta HRratio\ x\ \Upsilon$$

For this equation, D refers to the duration of exercise in minutes and Υ is a weighting factor for depending on if the athlete is male or female. $\Delta HRratio$ can be shown as:

$$w(t) = D\ x\ \Delta HRratio = \frac{HR_{ex} - HR_{rest}}{HR_{max} - HR_{rest}}$$

HR_{ex} is the average heart rate during exercise, HR_{rest} is the resting heart rate, and HR_{max} is the maximal heart rate. This equation provides a number which is given in arbitrary units and recorded for each training session. Utilizing this method requires the use of heart rate monitors for each training session, as well as requiring fairly steady-state activity(26). TRIMP may not be the best quantification method for football given the interval nature of the sport.

Another method which utilizes heart rate for calculating workload is the Summated Heart Rate Zone Score (SHRZS)(77). Instead of taking the average heart rate for the entire training session, as is done in TRIMP, the SHRZS takes the total number of minutes spent in five distinct

heart rate zones (50-60%, 60-70%, 70-80%, 80-90%, and 90-100% of HR maximum). Each of these zones was given a multiplying factor from 1 to 5, respectively. The resulting values are then summated to provide an overall score for the training session. This method provides more responsive values depending on the relative intensity of the training session. However, it too requires heart rate monitors to be worn consistently, and therefore may not be practical in a sport setting.

Session Rating of Perceived Exertion

To combat the issue of heart rate data being lost if athletes forgot to wear the monitors, or if the monitors had a technical failure, Foster et al.(88) introduced the Session Rating of Perceived Exertion (sRPE) metric. This calculation is an adaptation from Borg's Rating of Perceived Exertion(24). Borg introduced a scale which asks the participant to rate how difficult they feel an activity is, aka their perceived exertion. The original scale had a range of 6-20 and was shown to correlate with a participant's heart rate, usually by adding a 0 to the end of the reported RPE value to obtain current heart rate range, during both high intensity and steady-state exercise(25). For example, a reported score of 17 would indicate a HR of 170 beats per minute. However, this tool could not be used to directly measure heart rate due to the decline of maximum heart rate values with age(124). To simplify the scale, Borg introduced a 0-10 scale (CR-10) based on a category scale where values are based on verbal feedback(24). The CR10 scale has shown to be highly correlated with lactate levels in muscle and blood(175).

Foster utilized the CR10 scale to derive calculation of training session load without the requirement of heart rate monitors(88). To determine sRPE, athletes provide an intensity rating from 0-10 approximately 30 minutes after the cessation of training(88). This intensity rating is

then multiplied by the duration of the training session in minutes. While sRPE is found to be reliable and valid(58, 104, 111, 152, 199, 200, 213, 214), its correlation to TRIMP has varied in studies between r = 0.61 to r= 0.85(26, 121). In addition, several factors can affect the accuracy of the RPE rating, and therefore the sRPE value. These factors include athlete memory, cognition, and individual experiences(82). In spite of these cautions, due to the absence of measuring equipment and the simplistic calculation method, sRPE continues to be widely utilized in numerous studies and across an array of sports(26, 33, 58, 65, 81, 95, 99, 112, 114, 143, 149-151, 161, 184, 200, 204, 207, 214, 217-219).

Comparing the subjective sRPE model with the objective TRIMP and SHRZS models, Borresen and Lambert(26) found several differences in the calculated values, even though athletes were performing the same training. For example, the authors found that for athletes who spent a greater amount of time doing high-intensity exercise, the objective models overestimated the training load. Similarly, the subjective sRPE model underestimated training load for these athletes as well. On the contrary, athletes performing low intensity exercise may have underestimated objective values, or the subjective model may overestimate those values. The authors contend that the weighting system used in the SHRZS may provide physiologically inaccurate values for determining load. Borresen and Lambert reviewed the literature and found that this model had also not been validated(26). As a result of these findings, or because TRIMP and sRPE are simpler to calculate, SHRZS has not been as widely utilized. Instead, researchers and practitioners have continued to use the sRPE method to measure internal workloads.

Player versus Coach Perceptions of Workload

In a perfect world, the perception of workout intensity and volume, aka the training load, should be similar between the coach and their athletes. The studies assessing this agreement, however, are mixed. Impellizzeri et al. found correlation between coach prescribed training volume (measured via heart rate monitors) and the athlete sRPE to range between r = 0.5 - 0.85(121). This study assessed heart rate load using three different TRIMP calculations (Banister's, Edwards', and Lucia's). Both Edwards and Lucia utilized summated heart rate zone scores(77, 144). Edwards', however, utilizes five pre-set heart rate zone percentages based on an athlete's maximal heart rate(77). Lucia's calculation is based on an athlete's lactate threshold zone(144). Her calculation has three heart rate zones depending on if an athlete is pre-lactate threshold, within lactate threshold, or exceeding lactate threshold values. Impellizzeri et al. found similar results between the TRIMP methods in their study and again found moderate correlation between sRPE and Edwards' TRIMP (r = 0.5 - 0.85) depending on the athlete(121). Therefore, it would appear that the positive correlations between sRPE and planned training imply that sRPE is a useful measure for continuous monitoring of training programs.

Even though a few studies have found positive correlations between sRPE and planned training(50, 109, 121), several have found weak correlations when coaches and players both rated the perceived exertion of training sessions(15, 31, 213). Brink and colleagues(31) had coaches rate their intended exertion index for each session. They then had athletes provide their ratings after the completion of each session. Player-coach correlations were significantly weak ($p < 0.0001$) for intensity (r = 0.24), duration (r=0.49), and load (r=0.41). Players also reported higher intensity and training load for what were planned to be easy and intermediate practice days, while reporting lower intensity, duration, and training load for days that were intended to

be hard practices. Finally, they found that younger soccer players (U-17) reported sessions as being more difficult than their older counterparts (U-19). The authors concluded that these discrepancies could lead to maladaptation to training. The discrepancies between internal training load by coaches and athletes could be due to multiple explanations. Besides an athlete's age and experience(15, 31), reported sRPE scores could be based on accumulated fatigue as a result of excessive training or sleep loss(106). Another issue with these studies is that they span a season or less in length. As a result, definitive conclusions have not been determined.

External Quantification of Training Load

Recent developments in technology have led to the introduction of wearable devices which utilize global positioning systems and accelerometers to track athlete load(208). These devices are generally worn between the shoulder blades using compression garments. The loads calculated from these wearables are referred to as external load(208). Football is a game which contains numerous accelerations, decelerations, sprints, and collisions(220, 221). The wearable unit devices have shown to be reliable and valid for monitoring athlete activity for running-based sports(72, 100, 127, 135, 146, 183, 209). The accelerometer-based variables captured by these units (including jumps, changes of direction, and accelerations, and decelerations) have also been shown to be reliable(13, 14, 29, 132). These units have also been shown to be useful in a multitude of sporting contexts(14, 30, 53, 63, 177, 182, 188, 234, 235).

The most reported measure of external training load is Player Load (Catapult Innovations, Melbourne, AUS)(208). This metric is calculated as the sum of all accelerometer

movements in the three-dimensional plane. This is a unit-less quantification as is defined by the manufacturer as:

$$\text{Player/Body Load} = \sqrt{\frac{(\alpha_{y1} - \alpha_{y-1}) + (\alpha_x - \alpha_{x-1}) + (\alpha_z - \alpha_{z-1})}{100}}$$

Where, y refers to the forward/backward acceleration, x refers to lateral acceleration, and z refers to vertical acceleration. The prevailing theory behind this tool is that higher numbers of accelerations, in every plane, are associated with greater efforts by the athletes, and as a result incite greater stressors to their bodies(208).

Studies have generally supported the use of these wearables by showing moderate to high correlations to distance covered(39, 182) and athlete sRPE(39, 95, 222). However, due to the trivial correlation of Player Load to VO_2(13, 212), and its moderate correlation with heart rate(13, 212), Player Load, having been derived from a trunk mounted device, may measure a separate construct than these previously utilized measures(39, 190, 195). As Vanrenterghem and colleagues suggest, Player Load is measuring the activity, accelerations, and therefore biomechanical load of the body as a unit(208). Even though the movement of the limbs is being measured through the sway of the trunk, the trunk has the largest amount of mass and therefore provides the best way to derive the work taken by the whole body without the hassle for accelerometers on every limb(208). Although Player Load is small to moderately correlated with other measures of exercise intensity, it is correlated with other forms of workload quantification and is perhaps the most efficacious way to measure workload in an uncontrolled sporting environment(208).

Acute:Chronic Workload Ratio and Injury

With the advancement of wearable devices into the sports of rugby, Australian rules football, soccer, and cricket, a new method for assessing external workload was developed(114). Based on a simplified version of Banister's fitness-fatigue model, Hulin and colleagues began to investigate the relationship between recent training loads (~3-10 days) and chronic training history (~4-6 weeks). The authors dubbed the ratio of acute and chronic workload the acute:chronic workload ratio (ACWR)(114). Although myriad acute and chronic timeframes have been investigated(27), the most common timeframe for which the ACWR has been applied is a 1-week acute training load period and a 4-week chronic training load(48, 49, 59, 61, 65, 81, 107, 108, 114, 115, 125, 126, 148, 150, 157, 168, 169, 186, 219, 227); however, other ratios have also been utilized(36, 149, 156, 188, 204). Hulin and colleagues(114) retrospectively assessed five years of elite cricket bowlers and the relationship between the number of balls bowled per week and injuries. They found that bowlers with an acute workload of more than 200% of their chronic workload history had a relative risk for injury of 3.3 (95% CI: 1.50 – 7.25) compared to bowlers with acute workload values for that week similar to their chronic values ($p < 0.0001$)(114). The authors concluded that large increases in acute workload were associated with increased risk in elite cricket fast bowlers(114).

Several studies have compared total distance traveled in team sport training and its relation to injury(49, 115, 116, 204). Hulin et al. (115) found that rugby players with ACWR values between 1.23 and 1.61 had an increased risk of injury of 2.88 when they had less than 7 days of rest between matches than those with ACWR ranges between 1.02-1.22(115). Even more striking, they found that athletes whose ACWR values exceeded 1.62 had a relative risk of 5.80 compared to those with normal values between 1.02-1.22. These results were supported by

other studies of Australian rules football players, which found total distance ACWR values greater than 2.00 led to higher relative risks of injury (4.87 – 8.41) compared to values less than 1.50(168, 169).

Total distance has not been the only metric through which ACWR was viewed. Although definitions of speeds varied, numerous studies looked at the total distance traveled at high speeds and the relationship with injury(36, 48, 61, 81, 125, 149, 168, 169, 204). Murray et al.(168) found that ACWR ratios greater than 2.00 for total distance covered while running 18.01 to 24.00 kilometers per hour (11.18 to 14.9 miles per hour) were associated with a relative risk increase of 4.66. High speed running (HSR) ACWR of greater than 2.00 have been found to be associated with increased risk in both the current week and the following week (RR = 4.36-9.63) (169). Studies from other sporting contexts have also supported these findings(49, 125, 149). However, there have been studies which reported nonsignificant findings with respect to injury risk when speeds greater than 20 km/h (12.4 mph) were analyzed(61, 204). Esmaeili et al. (81) also found that including recent leg injuries (<53 days) as a variable increased the hazards ratio of high ACWR from 1.57 to 4.60. As a result, the applicability of the ACWR with respect to distance covered at high speeds, measured using the GPS component of the wearable device, and remains mixed.

The Player Load metric (PL), as discussed earlier, is the value given from the cumulative accelerometer measurements instead of the GPS component of these wearable devices(13). This value has also been studied with respect to the ACWR equation(61, 81, 168, 169, 188). ACWR values greater than 2.00 increased current week injury risk (RR = 5.80 – 12.46) compared to normal ACWR values(168, 169). The accelerometer components can also provide measures for the number of accelerations, decelerations, and pitches thrown in sport. ACWR of acceleration

efforts between 0.86 and 1.22, and deceleration efforts between 0.86 and 1.12, were shown to decrease the chance of injury (Odds Ratio = 0.39) when the ACWR of these values was less than 0.86(169). Cummins et al. (61) also found that acceleration and deceleration measurements had a significant relationship with decreased injury (p = 0.001 and p = 0.037 respectively). These findings would seem to support the injury framework of this thesis where prescribing workloads that over-stress an athlete's tissues or systems would increase their risk of injury as a result of an inability to repair damaged tissues prior to the next training stimulus.

Session RPE and Injury

The ACWR, using the sRPE score as an indicator of internal load, has been widely studied due to its cost effectiveness and ease of implementation(48, 49, 65, 81, 125, 126, 148, 150, 151, 156, 157, 186, 204, 219). Malone et al. (150) utilized this method to assess injury relationships in pre-season and in-season Australian rules football players. They found that ACWRs greater than 1.50 may increase injury risk higher during the pre-season period (OR = 3.03) than the in-season period (OR = 2.33)(150). Another study by Malone et al. (151) found that first-year elite Gaelic football players were at higher risk of injury than more experienced players (OR = 0.20 – 0.24). The authors commented that there may be a bell curve with respect to the relationship between loading rates and injury rates(151). Other sRPE-based ACWR studies found similar findings with ACWRs greater than 1.50 and increased injury rates(36, 156, 157, 219). Although it seems conclusive, results of some studies have contradicted the previously mentioned results. Colby et al. (49) found that ACWR values greater than 1.30 were associated with decreased injury incidence rate ratio (IRR = 0.93). Other studies found no association between the traditional ACWR and injury(65, 186).

Other studies using sRPE-based ACWR have sought to understand if the acute load was responsible for increased injury risk or if low chronic loads were. Stares et al. (204) found that the presence of very low chronic workloads for distance, sprint distance, and sRPE increased the risk of injury at 7, 14, 21, and 28 days after the spike in ACWR (RR = 2.71 – 6.93). Injury risk was also elevated when low chronic sRPE workloads were combined with low acute sRPE loads when compared to the normal ACWR range of 0.90 to 1.20 (RR = 2.15 – 2.38). Low chronic sRPE load combined with low ACWR was also likely increased injury incidence rate ratio (IRR = 2.52) compared to normal loads in the study by Colby et al. (49). However, it should be noted that this study listed "low" ACWR as 0.86 to 1.02, which is defined as normal in the Stares et al. study(204).

Maupin and colleagues(155) combined seven studies(114, 116, 149-151, 168, 169) to produce pooled effect sizes for total distance, sRPE, high speed running, PL, and moderate speed running. The combined effect sizes display a trend for lower risks of injury when ACWR ranges from 0.80 to 1.30(155). They also that those athletes with ACWR greater than 2.00, showed higher risk of injury than those with lower ACWR values (OR = 4.00, 95% CI = 1.65-9.68) (155). Relative risks also ranged from 3.91 to 8.90 when ACWR was greater than 2.00. Interestingly, they also noted that ACWRs less than 0.80 had increased injury risk (RR = 3.57, 95% CI = 1.65-9.68). Even though not all variables were equally represented across the seven studies analyzed(155), these results begin to suggest that the ACWR could be a useful way for coaches to periodize their training plans in order to provide the optimal balance between training stimulus and tissue recovery.

Comparing Internal and External Training Load

There have been a multitude of studies examining the relationship between internal and external load measures in team sports(16, 38, 39, 57, 95, 143, 184, 189, 190, 195, 196, 198, 203, 217, 218, 223). These studies have found correlations ranging from trivial to very large. A meta-analysis by McLaren and colleagues(161) synthesized these results and provided pooled estimates of the relationships. They found that the measures of internal load derived from perceived exertion and from heart rate are positively associated with external loads derived from GPS and accelerometer modalities(161). However, the magnitude and uncertainty of the relationships appear to be dependent on assessment tool and training mode(161). Total distance, it turns out, had the strongest associations with internal load and intensity indicators. The authors also noted that accelerometer-derived impacts (i.e., physical collisions, static exertions, jumping, etc.), which are pertinent to the sport of football, may have greater influence on sRPE and TRIMP scores than total distance.

Exponentially Weighted Moving Average Acute:Chronic Workload Ratio

Recently, the validity of ACWR has been questioned because, mathematically, the rolling average fails to account for the ability of fitness and fatigue effects to decay over time(68, 163, 228). Therefore, the ACWR value given may not accurately represent the variability in which loads are experienced over the past four weeks. Williams et al.(228) offered an alternative calculation which uses exponentially weighted moving averages (EWMA) for both acute and chronic loads. This calculation method known as EWMA ACWR, or EWMA for short, assigns a decreasing weight to compensate for the latency effects of load(228). The EWMA is calculated

daily for both acute and chronic workloads. The first activity is usually arbitrarily entered as the starting chronic value(161, 168, 188, 189). The equation used to calculate the acute period is:

$$\text{Acute: } EWMA_t = \left[Load_t * \left(\frac{2}{7+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{7+1}\right)\right] * EWMA_{t-1}\right\}$$

The equation used to calculate the chronic period is:

$$\text{Chronic: } EWMA_t = \left[Load_t * \left(\frac{2}{21+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{21+1}\right)\right] * EWMA_{t-1}\right\}$$

The acute period is divided by the chronic to give a ratio value for each day.

The EWMA has been utilized in several sports(81, 126, 168, 227, 228) including American football(188). Studies comparing EWMA and traditional ACWR equations have found that while both methods demonstrate increasing injury risk with higher values, the ACWR method underestimates the risk of injury at higher values compared to EWMA(81, 126, 168, 188, 227). For example, a prospective study of 55 elite Australian rules football players over two seasons compared ACWR and EWMA methods(81). These authors found that the athletes with ratio values greater than 1.50 had higher hazard ratio with the EWMA calculation versus the ACWR method (6.8 vs 2.2 respectively). They concluded that EWMA provided ratio values that better explained injury occurrence than the ACWR method because it accounted for the physiological decay of training over time(81).

To date, there have only been 2 studies with American football players utilizing the ACWR and EWMA methods for calculating training load and injury risk(188, 189). The first paper by Sampson et al.(188) retrospectively modeled the best fitting workload ratio equation for the activity, measured using PL, and non-contact injury data accumulated by 52 athletes from one team over one pre-season and in-season period. Of the 52 players observed, 46 of them sustained injuries, which accounted for 105 total non-contact injuries. Thirty-one of these

injuries resulted in subsequent time-lost from activity. These authors utilized various acute and chronic timeframes and determined that the EWMA method, with a 7-day acute to 21-day chronic timeframe and a 3-day lag, resulted in the best fitting model ($R^2 = 0.54$). Football players were likely to be at a greater risk of injury when their EWMA value was greater than 1.30 compared to values between 0.80 and 1.30 (RR = 3.33, 95% CI = 1.35 – 8.19) and values less than 0.80 (RR = 3.05, 95% CI = 1.38 – 6.76). Their work also supported the concept that a low training base, measured with low chronic workload accumulation, combined with a high EWMA value, placed athletes at the highest risk of injury (RR = 30.67, 95% CI = 3.03 – 310.51).

The second paper by Sampson et al.(189) assessed the combined effect of workload ratios and self-reported wellness. These authors retrospectively assessed data from 42 college football players over the course of a competitive season. Data collected included injuries, wellness questionnaire scores, and PL using the 7:21 day EWMA method(189). Findings from this study revealed that high EWMA ACWRs were trivially associated with worse feelings of wellness, soreness, and fatigue. Although high EWMA ACWRs increased injury risk and negatively impacted wellness, athletes with the highest risk were the ones that reported high EWMA ACWR numbers combined with “better” wellness reports. These authors concluded that athletes may be able to self-modulate during their training sessions if they are feeling fatigued. Broad application of these results to the greater football community should be cautioned due to the retrospective nature of this study examining one team and only during the in-season period of sport participation. Therefore, analyses using larger data sets, over multiple years, and with multiple teams are warranted.

Criticisms of Current Workload Research

Even though the past research done using the EWMA and ACWR methods to assess injury risk have been promising, including being drafted into an International Olympic Committee statement(201), serious criticisms of the methodologies and conclusions drawn from this line of research have emerged(36, 142, 173, 174, 216). The most basic criticism has been how loads have been measured(216). Internal and external workloads, as discussed previously, have been measured using an assortment of variables(102, 155, 161). Due to this inconsistency in observed variables, results from one study are often heterogenous and non-applicable to others(118). In addition, the definition of injury is not constant across every study(36, 48, 49, 61, 65, 81, 107, 114-116, 125, 148-151, 155, 156, 167-169, 186, 188, 189, 204, 207, 216, 219, 230). Other criticisms attack the basis on which the ACWR is calculated.

The explanation that ACWR is a measure of change has also been a topic of debate(216). Wang et al.(216) contend that the conventional measure of ACWR is proportion because it measures the amount that the acute workload represents in relation to the whole and not a true measure of change. Because the acute load is traditionally included in the chronic load, critics contend that this causes the values to be "mathematically coupled" and results in spurious correlations(142, 216, 231). This coupling in effect places a theoretical maximum value for ACWR of 4.00. This has implications if an athlete has not trained in the past three weeks and then begins activity. Regardless of how much activity the athlete actually performs in the acute week, whether they run 1 mile or 100 miles, their ACWR value can be a maximum of 4.00. Using an uncoupled method would remove the correlation and increase the between-athlete variability(142). The uncoupled ACWR also has its limitations(216). Wang et al.(216) contend that the acute and chronic values should be separate variables in order to determine whether any

observed relationship with injury is due to the ratio, the chronic load, or both. Others assert that the relationship between the acute and chronic loads may not be linear(8, 62). Further research is needed before the efficacy of the ACWR model can be determined.

The EWMA method has also drawn its fair share of criticism(163, 216). While the EWMA may better reflect changes in activity better than the ACWR(102, 188), the logistic regression used to draw this original conclusion did not account for repeated measures of the same individuals(216). Furthermore, given the decay nature of this equation, modeling days closest to Day 0 has a large effect on the weights of subsequent days(216). Therefore, it is important for observation periods to extend beyond a couple months before drawing relationships between workload and injury(216). This will allow the convergence of the ratio regardless of the starting values being positive or zero(216). However, this convergence would only take place for athletes who were un-injured during the first 50 days of training(216).

The concept of tapering is also negatively reflected in the EWMA model. Several sports incorporate a taper towards the end of a season and into the post-season(166). Tapering is the planned reduction of activity in order to reduce fatigue and increase recovery, with the objective to optimize performance and minimize injury risk(31, 73, 166, 208). College football could also taper as they transition from the regular season and train for their bowl game. However, the EWMA model will represent this taper as a higher ACWR during competition(216). Wang and colleagues contend that a different model and set of recommendations, which have yet to be defined, be used for these instances(216).

Perhaps the greatest critique of the studies utilizing the ACWR and EWMA methods has been the discretizing of these continuous ratio values(36, 216). Discretizing this variable can result in the loss of the true relationship between the ratio and injuries(20). As was the case with

injury definitions, studies have binned this variable incongruently, as well as used various reference values for comparison, both of which make it difficult to generalize findings(49, 149, 151, 169). This discretization can also amplify data from limited samples(216). When ACWR is separated into categories and assessed for a binary outcome variable, such as injuries, there is a requirement that at least 5 injury observations be present for each category(101). This is amplified when covariates (i.e., pre-season, in-season, position, etc.) are included in the model(216). Specific injury counts per category were also not reported, or have been underpowered for discretized analysis(216). For example, Wang and colleagues demonstrated that the traditional ACWR model used in the IOC consensus statement(201) was based on only three studies, and only one of the studies reported any injury count at all(216).

To better understand the predictive abilities of these models, Carey et al.(36) compared computer models of training load and injuries using both discretized and continuous methods, which used large sample sizes and simulated repeat studies. They found that discretized models had a false discovery rate of 16-21%, whereas continuous models using either spline regression or fractional polynomials, had rates of only 3-7%(36). Two of the three discretized models also had higher false rejection rates (57-59%) compared to the continuous models (12-19%). These authors suggested that future research utilize longitudinal data which accounts for repeated observations, achieve adequate statistical power, and use continuous methods to assess the relationships of these workload ratios and injuries(36). Nielson et al.(173) also recommend sports injury researchers collaborate with statisticians or methodological epidemiologists to best model causal relationships.

Summary of Current Evidence and Future Directions

In conclusion, there is substantial evidence linking measures of both internal and external workload to increased injury risks in various sporting populations. However, without improvements in statistical methodologies and the detail in outcome reporting, drawing definitive and generalizable conclusions from these measures is limited. Furthermore, studies in American football have not assessed the association between these measures and non-contact injuries throughout the entire training cycle.

The current studies aim to assess the relationship of these workload ratio models to non-contact injuries in American football. These studies will assess these relationships across years and teams. They will also assess the concept, purposed by the injury model earlier, that spikes in workload will result in increased inflammation, measured from CRP, and that this inflammation will precede non-contact injury.

CHAPTER 3

A MULTI-TEAM ASSESSMENT OF EXTERNAL WORKLOAD MODELS AND ASSOCIATIONS WITH INJURY RATES IN NCAA AMERICAN COLLEGE FOOTBALL

ABSTRACT

Recent research has shown associations between sudden changes in workload with subsequent injury in NCAA Division 1 American football players. However, these findings were based on data from a single team during a single pre-season and in-season period. **PURPOSE:** To assess the relationships among workload, workload ratios, phases of sport participation, and non-contact injury occurrence across two football teams over a two-year period. **METHODS:** Movement and injury occurrence data derived from 120 football players from two NCAA Division 1 football teams during the 2018 and 2019 seasons were retrospectively analyzed. Movement data, measured using wearable devices, were collected for the summer conditioning, pre-season practice, and in-season periods. Workload ratios were calculated using both the 7-day:28-day rolling averaged acute:chronic workload ratio (ACWR) and the 7-day:21-day acute:chronic workload ratio utilizing exponentially weight moving averages (EWMA). Workload data (arbitrary units; AU) from the spring practice phase of training were used to provide workload ratios at the beginning of summer conditioning period. All injuries were classified by the respective medical staffs. Lower-body and trunk injuries with a non-contact or overuse mechanism, and that resulted in time away from training or competition, were included in the analysis. Injury incidence rate ratios (IRR) per 1000 hours (HEs) and per 1000 activity sessions (AEs) were calculated. Previous 7-day cumulative load (weekly load) was calculated daily. Kruskal-Wallis H tests for workload and workload ratios were conducted by team and phase. Both combined and team-specific generalized estimating

equation (GEE) models were developed. Weekly load and workload ratio variables were standardized by phase of year then assessed for model inclusion. Models were selected by quasilikelihood under the independence model criterion (QIC). GEE results were presented as odds ratios (OR) and injury probabilities. Models were evaluated by using area under the curve (AUC) values for both Receiver Operating Characteristic (ROC) and Precision-Recall (P-R) curves. **RESULTS:** A total of 88 non-contact/overuse injuries were recorded, with 23 (0.79 HEs; 1.22 AEs) resulting in time-loss. The hip/thigh region had the largest injury count (54 total; 9 time-loss) and HE (1.85). Preseason practice had the largest AE (3.33). The overall average and standard deviation for weekly load was 1215 $\pm$ 477 AU. The average ACWR and EWMA ratios were 1.21 $\pm$ 0.73 and 0.86 $\pm$ 0.37, respectively. Workload and workload ratios in each phase differed significantly by team except for summer conditioning. GEE models were all statistically significantly associated with non-contact time-loss injuries for each team, with Wald χ^2 values ranging from 7.54 to 1624.20 depending on the model workload ratio, phase of year, and dataset used. Though odds ratios varied by model, in general there was an inverted-U relationship between workload ratios and injury. The weekly load covariate in these models was also associated with lower injury probability with ORs ranging from 0.07 to 0.18 ($p < .005$). ROC AUC failed to reject the H_0 that the 4 models were equivalent (Team 1: $\chi^2 = 4.53$, $p = 0.21$; Team 2: $\chi^2 = 5.12$, $p = 0.16$). P-R AUC ranged from .0070 to .0237 depending on the model, which suggests that these models have low precision and recall. **CONCLUSION:** EWMA and ACWR models were associated with non-contact time-loss injuries, however the inverted-U relationship to injury probability displayed in these models is counter to previous research. This study highlights the need for standardized injury classification and participation criteria.

Practitioners should not rely solely on these workload ratio models to plan training for optimized performance or rehabilitation.

INTRODUCTION

According to the National Collegiate Athletic Association (NCAA), approximately 29,000 football players compete at the NCAA Division 1 level each year(5). NCAA Division 1 American football (football) players are inherently exposed to the risk of injury(133, 137, 158, 225, 229). The rate of injury has been observed to range from 3.17 to 4.90 per 1,000 athlete practice and game sessions(225). Injuries resulting in lost participation time are often cited as major contributors in overall team success(69, 87, 123). Time-loss injury rates in collegiate football have been calculated to 2.4 per 1,000 snaps(158) and 7.14 per 1,000 athlete practice and game sessions (133). Mitigating injury occurrence is important for both athlete health and overall team success(69, 87, 123). To minimize injury risk and maximize team success, schools have begun to utilize wearable devices to capture information regarding player workload. These devices combine global position systems and accelerometers to quantify and assess athlete movements (workload) during conditioning, practices, and games.

Workload can be categorized into acute (most recent 7 days) and chronic (previous 3- to 4-weeks) values. These values can be referenced as a ratio, which can then be utilized to measure the rate of increase or decrease of an athlete's current training relative to their training history. The value for this ratio has been calculated using various mathematical approaches(102, 155). The two most common are the original 7-day acute to 28-day chronic method, which utilizes rolling averages (ACWR) (114), and the 7-day acute to 21-day chronic method with exponentially weighted moving averages (EWMA) (102, 155, 228). These are the most common

calculation methods reported in the literature due to the relative ease of calculation, as well as the use of weeks as the principal time frame. To date, several studies have found associations between large deviations in acute workload from chronic values and subsequent injury occurrence(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 188-190, 195, 196, 198, 203, 207, 217, 218, 223).

Sampson and colleagues(188) found that in college football, the 7:21-day coupled acute:chronic workload ratio calculated using an exponentially weighted moving average (EWMA) with a 3-day injury lag period had the greatest association to injury occurrence. Although this model is beneficial to guide practitioners in program design and player monitoring, it is important to expand upon this research with a larger participant pool and utilize multiple teams. Longer studies with multiple teams and more athletes will improve the validity of the results by minimizing the impact of individual, team, and time effects in the data(154). Furthermore, previous research on the workload-injury association has been criticized for suboptimal statistical analyses(36, 216). Therefore, the purposes of this study are to 1) compare the relationships among workloads, workload ratios, injury rates, and phases of training across two teams; and 2) determine if a workload ratio model consisting of data from two teams would be associated with non-contact injury-risk. We hypothesized that both teams will have similar workloads, workload ratios, and injury occurrences; but the values of these measures will be significantly difference across time. We also hypothesized that the EWMA workload ratio calculation will be more associated with non-contact injury risk than the ACWR calculation.

METHODS

Participants

Data were collected from college football players (n = 120) from two NCAA Division 1 varsity teams (mean ± SD: age: 20.7 ± 1.1 years, mass: 109.6 ± 23.2 kg, and height: 186.7 ± 8.3 cm). Each NCAA team volunteered to participate in the study and provide data which had already been collected. Football position groups were classified into three distinct categories: Skill (wide receivers & defensive backs), Big Skill (running backs, tight ends, and linebackers), and Power (offensive and defensive linemen). Quarterbacks and Specialists were not included in this study due to their unique practice and game environments. Athlete composition data are presented in Table 3.1. All players trained full-time with their team during the length of the observational period. The observational period took place from March 2018 thru December 2019. All participant workload and injury data were de-identified at their respective team site. Furthermore, data for each team were de-identified by a mutual third-party vendor (Catapult Innovations, Melbourne, AUS). All experimental procedures for this study were approved by the Michigan State University Human Research Protection Program.

Table 3. 1. Athlete composition data.

	All Time Periods			2018			2019		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Athletes	120	42	78	85	28	57	86	30	56
Skill	50	22	28	37	17	20	33	14	19
Big Skill	43	17	26	28	10	18	31	13	18
Power	27	3	24	20	1	19	22	3	19
	2018: Summer			**2018: Fall Camp**			**2018: Season**		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Athletes	75	28	47	79	28	51	83	28	55
Skill	34	17	17	36	17	19	36	17	19
Big Skill	23	10	13	24	10	14	27	10	17
Power	18	1	17	19	1	18	20	1	19
	2019: Summer			**2019: Fall Camp**			**2019: Season**		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Athletes	76	28	48	81	28	53	85	29	56
Skill	28	13	15	31	13	18	32	13	19
Big Skill	28	13	15	30	13	17	31	13	18
Power	20	2	18	20	2	18	22	3	19

Quantifying Workload

Wearable devices (Optimeye S5, Catapult Innovations, Melbourne, AUS) which combine 10Hz GPS with a 100 Hz tri-axial accelerometer, a gyroscope, and a magnetometer were worn throughout the study. These devices derive an external workload metric known as Player Load (Catapult Innovations). Previous research has established the reliability, construct validity, convergent validity of these devices, and the components that are used in their construction, with ground-based and standardized treadmill running (13, 57, 58, 100, 127, 132, 161, 183, 209, 214).

The S5 devices were placed in a compression garment worn by the players during all conditioning and non-padded practice sessions. These garments placed the devices between the

scapulae of the players. Garment sizes vary from small to xxxx-large to ensure a compressed, comfortable fit. During padded practices, players wore the devices in boxes mounted on their shoulder pads in a similar location to the vests. Players wore the same device during every conditioning and practice session. Following each session, the data were downloaded into the accompanying software (Openfield, Catapult Innovations, Melbourne, AUS). This software calculated workload as the sum of accelerations across all axes of a tri-axial accelerometer. This is a unit-less quantification and is defined by the manufacturer as:

$$\text{Player/Body Load} = \sqrt{\frac{(\alpha_{y1} - \alpha_{y-1}) + (\alpha_x - \alpha_{x-1}) + (\alpha_z - \alpha_{z-1})}{100}}$$

Each letter refers to either the forward/backward acceleration, lateral acceleration, or vertical acceleration. Workload rates were calculated using both the "traditional" 7-day:28-day rolling averaged acute:chronic workload ratio(114) (ACWR) and the exponentially weighted moving average (EWMA) calculation utilized in previous research(168, 188). For the EWMA model, the equation used to calculate the acute period was:

$$\text{Acute: } EWMA_t = \left[Load_t * \left(\frac{2}{7+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{7+1}\right)\right] * EWMA_{t-1}\right\}$$

The equation used to calculate the chronic period was:

$$\text{Chronic: } EWMA_t = \left[Load_t * \left(\frac{2}{21+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{21+1}\right)\right] * EWMA_{t-1}\right\}$$

Where 'Load' in this instance refers to the accelerometer-derived Player Load, t refers to the current observation, and *t*-1 refers to the previous observation. The acute period was divided by the chronic to give a ratio value for each day. In the event of missing data (248 of 18,909 activity observations; 1.3%), the activity average for the position group (i.e., defensive backs)

was imputed into the dataset pursuant to previous research(28, 188). Workloads calculated from spring were used for the acute:chronic workload calculations in the summer.

Definition of Exposure

Each conditioning, practice, and competition session was categorized as an activity. Athlete exposure was defined as one athlete participating in one of these activities. The participation in, and duration of, each activity was recorded within the accompanying software for the wearable devices. Practitioners for each team confirmed participation and durations for each athlete.

Definition of Injury

All injuries that occurred during the study period were classified by the respective sports medicine staff of that team. Injuries were categorized based on the NCAA Sports Injury Surveillance program(133). Lower-body and trunk injuries classified as non-contact or overuse in mechanism were included in the analysis due to possibly occurring because of large increases in activity exposure(87, 94). Time-loss was defined as any injury where an athlete was unable to participate in one or more conditioning sessions, practices, or competitions. Injury and movement data for each athlete were combined in a database, anonymized, and then sent to the mutual third-party vendor. The vendor then anonymized the school before sending the compiled data to the study coordinator. This process served to provide athlete descriptive data while also serving to provide an added layer of protection for athlete identifiable information from the study coordinator.

Statistical Analyses

All calculations and analyses utilized the Stata IC v16.1 software package (StataCorp LLC, College Station, TX). Athlete exposures were recorded as both the number of sessions and overall duration of participation in sport conditioning, practice, or games. Injury counts and participation were combined to calculate injury incidence rate ratios (IRRs). These IRRs, with 95% confidence intervals, are displayed as both per 1000 sessions (AEs) and per 1000 hours (HEs). Daily calculations of previous 7-day cumulative load (weekly load), ACWR, and EWMA ratio values were made for each athlete. Kolmogorov-Smirnov tests for normality were conducted and indicated non-normal distributions for each variable. Kruskal-Wallis tests were conducted to compare workload and workload ratios across teams and phases of year.

General estimating equation models were used to account for non-normality, probable intercorrelation between repeated observations for each athlete, and sparseness of non-contact injury occurrence. Athletes served as the repeated-measures unit and each day served as the observation unit. The binary outcome variable was specified to be a new non-contact injury occurrence. A logit-link function with a binomial error structure, and exchangeable correlation matrix was used to model the binary outcome variable.

Two models, one for each workload ratio calculation method, were developed. Each model considered the team, weekly load, and workload ratio values as covariates. Team-specific models were also created, in which case included observations were restricted to each team and the team covariate was removed from the model. Both the workload ratio and weekly load variables were standardized by subtracting the mean value of the variable and dividing by its standard deviation. These variables were standardized by each phase of the year. In accordance with suggestions by previous research, both linear-only and quadratic functions of each variable

were combined in the GEE models(36, 139). Unlike prior research, where observations were made weekly, and as such required a lag on the dependent injury occurrence in order to ensure sequentialty (139, 188), observations in this study were made daily so a lagged dependent injury outcome was not used. Because of the daily observations, only days where an activity (training session, practice, or competition) occurred were used in the analyses. A previous week load of zero would indicate an athlete being injured for a sustained period, and therefore would not be possible for them to experience a new injury. However, the daily workload ratios would still be calculated based on their in-activity. As a result, these observations were removed from the analyses. The quasilikelihood under the independence model criterion (QIC) was used to compare the linear and quadratic variations of each standardized variable in each model(60). QIC is an extension of Akaike information criterion (AIC), therefore the model with the lowest QIC value was deemed the best fit(60). Statistical analyses were represented by odds ratios (OR), Huber-White standard errors (SE), 95% confidence intervals (CIs), and with statistical significance set at $p < .05$. The generalized and team-specific EWMA and ACWR models were compared using Receiver Operating Characteristic (ROC) curves and Precision-Recall (P-R) curves. ROC curves serve to assess the diagnostic ability of the models to detect true injury occurrences versus false injuries. P-R curves are used to assess the diagnostic ability of the models to correctly identify injuries (positive outcomes) and are unconcerned with detecting true non-injury (negative outcomes). P-R curves are useful for datasets with an imbalance in outcomes such as those present in this study.

Power Analysis

We desired 80% power to detect a difference of at least moderate effect size (ES = 0.5) for workload and workload ratios between teams. Therefore, with the α level set at $\alpha = .05$ and 1 degree of freedom, a sample size of 32 players was required and was associated with a critical χ^2 value of 3.841. However, due to the unbalanced data set, we chose to include all observed athletes (n = 120), thus ensuring at least 32 players were observed for each time period.

RESULTS

Activity Summary

There were 37,332 total observations recorded spanning 487 days (mean $\pm$ SD: 380.6 $\pm$ 182.8 days per player). Activities were categorized as either conditioning or football. Football activities consisted of coach-led practices, scrimmages, and games, while conditioning consisted of strength coach-led running sessions. Activities accounted for 18,909 of the 37,332 total observations. Cumulative observations and activities by time of year and category are presented in Supplemental Table 3.1.

Total Injury Frequency and Injury Incidence Rate Ratios

During the observation period, 88 total non-contact injuries were sustained by 55 of the 120 athletes (45.8%). Each team recorded 44 non-contact injuries. Of these 88 injuries, 23 resulted in lost time (Team 1: 6; Team 2: 17). These 23 injuries were sustained by 22 athletes. A summary of the injuries by time-period and team are reported in Table 3.2.

Table 3. 2. Summary of injuries and injured athletes by time-period and team.

	All Time Periods			2018			2019		
Injuries (IDs)	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Non-Contact	88 (55)	44 (23)	44 (32)	49 (33)	23 (14)	26 (19)	39 (27)	21 (13)	18 (14)
Time-Loss	23 (22)	6 (5)	17 (17)	12 (10)	1 (1)	11 (9)	10 (9)	4 (3)	6 (6)
	2018: Summer			**2018: Fall Camp**			**2018: Season**		
Injuries (IDs)	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Non-Contact	14 (13)	5 (4)	10 (9)	16 (14)	8 (7)	8 (7)	19 (14)	11 (7)	8 (7)
Time-Loss	1 (1)	0 (0)	1 (1)	4 (4)	0 (0)	4 (4)	7 (6)	1 (1)	6 (5)
	2019: Summer			**2019: Fall Camp**			**2019: Season**		
Injuries (IDs)	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Non-Contact	10 (9)	6 (5)	4 (4)	10 (10)	6 (6)	4 (4)	19 (14)	9 (8)	10 (6)
Time-Loss	1 (1)	0 (0)	1 (1)	5 (5)	3 (3)	2 (2)	4 (4)	1 (1)	3 (3)

Injury incidence rate ratios (IRR) were determined by dividing the total number of non-contact and overuse injuries by exposure time and reported as both rates per 1000 hours (HEs) and rates per 1000 Athlete Exposure sessions (AEs). The total combined non-contact and overuse injury rate was 3.02 HEs (4.65 AEs). The rate for injuries resulting in time-loss from activity was 0.79 HEs (1.22 AEs). The site where the largest number of injuries occurred (54 total; 9 time-loss), and as a result had the largest injury rate (1.85 HEs; 2.86 AEs), was the hip/thigh region. A summary of injury counts and IRRs by site and diagnostic criteria are contained in Table 3.3.

Overall, the preseason camp period had the greatest non-contact time-loss injury incidence rate ratio (HE: 1.67; AE: 3.33). However, the summer conditioning period contained the largest occurrence of diagnosed non-contact injuries per hour of activity (HE: 6.95). A complete summary of time-loss IRRs by year and phase of season is compiled in Table 3.4. A full summary of all non-contact injuries is reported in Supplemental Table 3.2.

Table 3. 3. Non-contact (time-loss) injury characteristics and injury incidence rate ratios.

Injury Site	**Counts**			**Per 1000 Hours**			**Per 1000 Sessions**		
(Time-Loss)	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
All Sites	88 (23)	44 (6)	44 (17)	3.02 (0.79)	4.78 (0.65)	2.21 (0.85)	4.65 (1.22)	6.41 (0.87)	3.65 (1.41)
Trunk	3 (0)	2 (0)	1 (0)	0.10 (0.00)	0.22 (0.00)	0.05 (0.00)	0.16 (0.00)	0.29 (0.00)	0.08 (0.00)
Hip/Thigh	54 (9)	33 (3)	21 (6)	1.85 (0.31)	3.58 (0.33)	1.05 (0.30)	2.86 (0.48)	4.81 (0.44)	1.74 (0.50)
Knee	7 (2)	0 (0)	7 (2)	0.24 (0.07)	0.00 (0.00)	0.35 (0.10)	0.37 (0.11)	0.00 (0.00)	0.58 (0.17)
Lower Leg	8 (4)	4 (1)	4 (3)	0.27 (0.14)	0.43 (0.11)	0.20 (0.15)	0.42 (0.21)	0.58 (0.15)	0.33 (0.25)
Ankle	3 (0)	1 (0)	2 (0)	0.10 (0.00)	0.11 (0.00)	0.10 (0.00)	0.16 (0.00)	0.15 (0.00)	0.17 (0.00)
Foot	8 (6)	1 (1)	7 (5)	0.27 (0.21)	0.11 (0.11)	0.35 (0.25)	0.42 (0.32)	0.15 (0.15)	0.58 (0.41)
Other	5 (1)	3 (0)	2 (1)	0.17 (0.03)	0.33 (0.00)	0.10 (0.05)	0.26 (0.05)	0.44 (0.00)	0.17 (0.08)
Diagnosis	**All Time Periods**			**Per 1000 Hours**			**Per 1000 Sessions**		
(Time-Loss)	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Fracture	2 (2)	0 (0)	0 (0)	0.07 (0.07)	0.00 (0.00)	0.10 (0.10)	0.11 (0.11)	0.00 (0.00)	0.17 (0.17)
Sprain	11 (4)	1 (0)	10 (4)	0.38 (0.14)	0.11 (0.00)	0.50 (0.20)	0.58 (0.21)	0.15 (0.00)	0.83 (0.33)
Strain	66 (12)	42 (5)	24 (7)	2.27 (0.41)	4.56 (0.54)	1.20 (0.35)	3.49 (0.63)	6.12 (0.73)	1.99 (0.58)
Other	9 (4)	1 (0)	8 (4)	0.31 (0.14)	0.11 (0.00)	0.40 (0.20)	0.48 (0.21)	0.15 (0.00)	0.66 (0.33)

Table 3. 4. Injury incidence rate ratios (IRR) by year and phase of season.

	Phase	Per 1000 Hours (95% CI)	Per 1000 Sessions (95% CI)
2018	**Combined**	0.66 (0.00, 1.51)	1.06 (0.00, 2.51)
	Summer	0.52 (0.00, 1.54)	0.50 (0.00, 1.47)
	Camp	1.05 (0.00, 3.10)	2.32 (0.00, 6.88)
	Season	0.59 (0.12, 1.06)	1.03 (0.28, 1.79)
2019	**Combined**	0.72 (0.50, 0.94)	1.03 (0.98, 1.08)
	Summer	0.41 (0.00, 1.21)	0.49 (0.00, 1.44)
	Camp	2.43 (0.00, 4.92)	4.45 (0.82, 8.08)
	Season	0.37 (0.23, 0.50)	0.58 (0.31, 0.86)
ALL	**Combined**	0.69 (0.33, 1.05)	1.14 (0.62, 1.67)
	Summer	0.46 (0.00, 1.35)	0.49 (0.00, 1.46)
	Camp	1.67 (1.63, 1.72)	3.33 (2.64, 4.02)
	Season	0.48 (0.17, 0.79)	0.80 (0.26, 1.34)

Activity Loads and Workload Ratios

The average ± standard deviation for weekly load during the investigation period was 1215 ± 477 AU. Average ACWR and EWMA ratio values were 1.21 ± 0.73 and 0.86 ± 0.37, respectively. The pre-season camp period had the largest weekly workloads (1917 ± 391) and EWMA values (1.12 ± 0.21), while the summer conditioning period had the largest ACWR values (1.62 ± 1.22). Boxplots of weekly workload by team and season are displayed in Figure 3.1 and demonstrate a large increase at week 32 which is the first full week of pre-season practice. Weekly load then has minor fluctuations during the in-season phase which takes place from weeks 35 thru 52. Figure 3.2 contains boxplots of weekly workload ratios by team and season and mirrors the same trends displayed in Figure 3.1. Additionally, detailed average weekly load and workload ratios by year and phase of season are included in Table 3.5.

Table 3. 5. Average weekly load and workload ratios by year and phase of season

Weekly Load (AU ± Std. Dev.)	**Combined**			**2018**			**2019**		
	Summer	**Camp**	**Season**	**Summer**	**Camp**	**Season**	**Summer**	**Camp**	**Season**
Combined	719 ± 350	1917 ± 391	1307 ± 249	709 ± 352	1881 ± 434	1287 ± 284	730 ± 362	1951 ± 426	1326 ± 322
Team 1	756 ± 294	1478 ± 340	1129 ± 254	781 ± 304	1565 ± 288	1008 ± 295	732 ± 338	1392 ± 460	1248 ± 319
Team 2	697 ± 417	2165 ± 456	1405 ± 276	665 ± 436	2066 ± 533	1440 ± 365	729 ± 423	2260 ± 514	1369 ± 356
Workload Ratio (AU ± Std. Dev.)	**Combined**			**2018**			**2019**		
	Summer	**Camp**	**Season**	**Summer**	**Camp**	**Season**	**Summer**	**Camp**	**Season**
Combined: ACWR	1.62 ± 1.22	1.36 ± 0.53	0.97 ± 0.21	1.58 ± 1.21	1.39 ± 0.55	0.97 ± 0.21	1.58 ± 1.21	1.39 ± 0.55	0.97 ± 0.19
Combined: EWMA	0.99 ± 0.35	1.12 ± 0.21	0.91 ± 0.10	0.99 ± 0.35	1.12 ± 0.21	0.91 ± 0.10	1.01 ± 0.37	1.12 ± 0.21	0.92 ± 0.10
Team 1: ACWR	1.57 ± 1.11	1.23 ± 0.53	0.96 ± 0.21	1.59 ± 1.13	1.23 ± 0.49	0.96 ± 0.22	1.55 ± 1.09	1.22 ± 0.56	0.97 ± 0.26
Team 2: ACWR	1.66 ± 1.32	1.45 ± 0.57	0.98 ± 0.24	1.55 ± 1.28	1.48 ± 0.60	0.98 ± 0.25	1.75 ± 1.38	1.41 ± 0.57	0.97 ± 0.21
Team 1: EWMA	1.09 ± 0.37	1.08 ± 0.21	0.93 ± 0.12	1.11 ± 0.38	1.09 ± 0.21	0.93 ± 0.14	1.08 ± 0.36	1.07 ± 0.22	0.94 ± 0.13
Team 2: EWMA	0.93 ± 0.39	1.14 ± 0.26	0.90 ± 0.11	0.96 ± 0.39	1.14 ± 0.24	0.91 ± 0.13	0.90 ± 0.45	1.15 ± 0.30	0.88 ± 0.14

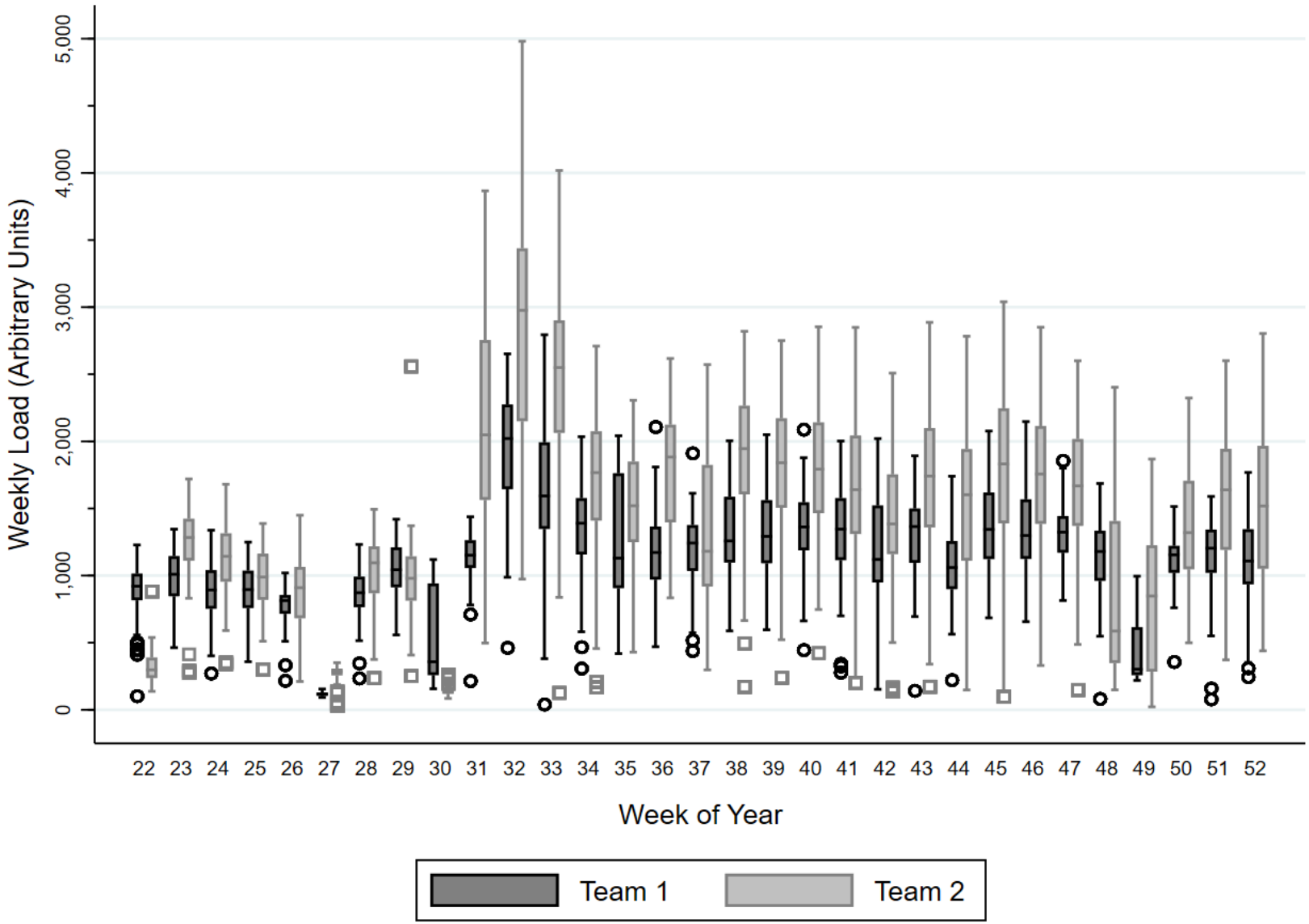

Figure 3. 1. Weekly load by team and week of year.

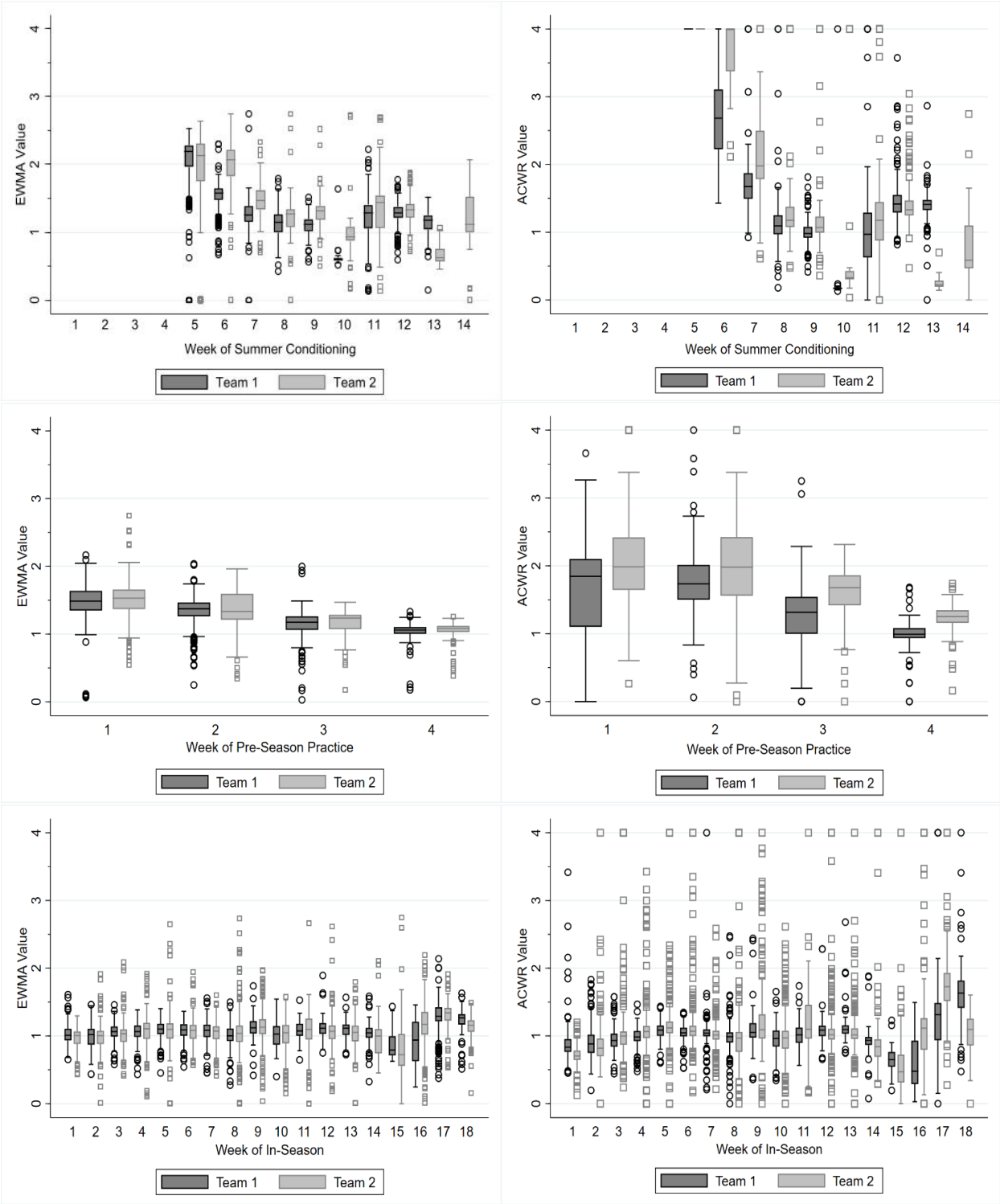

Figure 3. 2. EWMA and ACWR values by team and phase of year.

Kruskal-Wallis tests for workload and workload ratios demonstrated that overall group medians were statistically significantly different (Table 3.6). Therefore, we rejected the H_0 that Team 1 and Team 2 possessed overall similar data. These results held for the pre-season (χ^2: 749.470, $p < .005$) and in-season (χ^2: 1453.146, $p < .005$) phases when assessed individually, however, we failed to reject H_0 for the summer conditioning period (χ^2: 3.132, $p < .077$). The Kruskal-Wallis tests to determine differences by phase of year were statistically significant for both combined and team-specific data sets (Supplemental Table 3.3). Post-hoc pairwise comparisons were performed using Dunn's procedure(74) with a Bonferroni correction for multiple comparisons. This analysis revealed statistically significant differences between summer conditioning, pre-season practice, and in-seasons phases for workload and workload ratios. Effect sizes were assessed post-hoc by calculating partial eta-squared (η^2) from the Kruskal-Wallis H statistic(141) and are reported in Table 3.6.

As a result, our hypothesis was correct that workload and workload ratios would differ across time. However, our hypothesis that both teams would have similar workloads and workload ratios for each phase of the year to each other was incorrect, as the pre-season and in-season periods were significantly different between the two teams.

Table 3. 6. Kruskal-Wallis H test results for team differences.

Team Comparison	**Workload**			**ACWR**			**EWMA**		
	X^2	**Deg.**	***p*-value**	**X^2**	**Deg.**	***p*-value**	**X^2**	**Deg.**	***p*-value**
Summer Conditioning	3.13	1	.077	17.15	1	$< .005^t$	68.03	1	$< .005^t$
Pre-Season Practice	749.47	1	$< .005^t$	350.31	1	$< .005^t$	51.93	1	$< .005^t$
In-Season	1453.15	1	$< .005^t$	4.61	1	$.032^t$	34.42	1	$< .005^t$

Abbreviation: Deg, degrees of freedom in chi-square test. Note: t denotes statistically significant results at $p < .05$ level.

Generalized Estimating Equation Models

For ACWR and EWMA GEE models, the inclusion of the quadratic of the workload ratio and the linear weekly load yielded the lowest QIC score for both the combined and team-specific datasets and were selected for further analysis. A full comparison of each model, including the number of parameters, the trace value, and corresponding QIC score is reported in Table 3.7.

Table 3. 7. QIC results for GEE models by dataset.

Model	Variables	P	Trace	QIC
Combined EWMA	EWMA, Weekly Load, Team	4	3.433	442.969
	EWMA^2, EWMA, Weekly Load, Team	**5**	**5.201**	**358.360**
	EWMA, Weekly Load^2, Weekly Load, Team	5	4.400	446.991
Combined ACWR	ACWR & Weekly Load, Team	4	3.483	379.693
	ACWR^2, ACWR, Weekly Load, Team	**5**	**5.657**	**356.733**
	ACWR, Weekly Load^2, Weekly Load, Team	5	4.346	384.530
Team 1 EWMA	EWMA & Weekly Load	3	2.599	414.339
	EWMA^2, EWMA, Weekly Load	**4**	**4.277**	**349.946**
	EWMA, Weekly Load^2, Weekly Load	4	3.547	432.307
Team 1 ACWR	ACWR & Weekly Load	3	2.801	388.811
	ACWR^2, ACWR, Weekly Load	**4**	**4.708**	**374.607**
	ACWR, Weekly Load^2, Weekly Load	4	3.691	406.367
Team 2 EWMA	EWMA & Weekly Load	3	2.329	459.879
	EWMA^2, EWMA, Weekly Load	**4**	**4.107**	**384.005**
	EWMA, Weekly Load^2, Weekly Load	4	3.282	460.308
Team 2 ACWR	ACWR & Weekly Load	3	2.289	388.818
	ACWR^2, ACWR, Weekly Load	**4**	**3.990**	**369.831**
	ACWR, Weekly Load^2, Weekly Load	4	3.055	388.350

Abbreviation: P, number of parameters including dependent variable; QIC: quasilikelihood information criterion statistic. Note: All variables were standardized by phase of year before model initiation. Models in bold were selected for further analysis.

Both combined and team-specific GEE models were statistically significant at the $p < 0.05$ level. In the combined dataset, EWMA and ACWR models had Wald χ^2 values of 42.40 ($p < 0.005$) and 32.49 ($p < 0.005$), respectively. The Team 1-specific models did not converge for the summer period, which was likely due to only observing one injury in that phase of training. The only subset of data where the Wald χ^2 statistic was computed but did not achieve significance at the $p < .05$ level was the Team 1-specific EWMA model of pre-season observations. Here the Wald χ^2 statistic was 7.54 and corresponded to a *p*-value of .057. The Wald χ^2 statistic and associated *p*-value for each model is reported in Supplemental Table 3.5. All other subsets of data were statistically significant.

The weekly load covariate in each model was statistically significant and associated with decreased odds of sustaining an injury. The significance of the workload ratio and its quadratic varied by model. In each instance, however, the linear component of the workload ratio was associated with larger odds of injury, while the quadratic was associated with lower odds of injury. Variable- and model-specific results including odds ratios, 95% confidence intervals, Huber-White standard errors, z-scores, and *p*-values are presented in Table 3.8.

Table 3. 8. GEE results by model and variable.

Combined EWMA Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
EWMA^2	0.23	0.09 – 0.61	0.11	-2.98	< 0.005
EWMA	1.44	0.49 – 4.26	0.80	0.66	0.511
Weekly Load	0.15	0.06 – 0.36	0.07	-4.22	< 0.005
Team 1	0.41	0.15 – 1.09	0.20	-1.79	0.073
Combined ACWR Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
ACWR^2	0.77	0.54 – 1.12	0.15	-1.37	0.172
ACWR	2.12	0.98 – 4.62	0.84	1.90	0.058
Weekly Load	0.13	0.06 – 0.30	0.06	-4.82	< 0.005
Team 1	0.46	0.18 – 1.20	0.23	-1.58	0.115
Team 1 EWMA Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
EWMA^2	0.28	0.03 – 3.07	0.35	-1.04	0.301
EWMA	1.72	0.42 – 7.11	1.25	0.75	0.452
Weekly Load	0.07	0.01 – 0.41	0.06	-2.96	< 0.005
Team 1 ACWR Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
ACWR^2	0.84	0.39 – 1.85	0.34	-0.42	0.671
ACWR	1.31	0.45 – 3.86	0.72	0.50	0.620
Weekly Load	0.09	0.02 – 0.41	0.07	-3.13	< 0.005
Team 2 EWMA Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
EWMA^2	0.22	0.08 – 0.61	0.11	-2.90	< 0.005
EWMA	1.39	0.35 – 5.48	0.97	0.47	0.641
Weekly Load	0.18	0.07 – 0.48	0.09	-3.44	< 0.005
Team 2 ACWR Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
ACWR^2	0.71	0.51 – 0.99	0.12	-2.02	0.043
ACWR	2.68	1.17 – 6.14	1.13	2.33	0.020
Weekly Load	0.15	0.06 – 0.37	0.07	-4.09	< 0.005

Abbreviations: 95% CI, 95% confidence interval number of parameters including dependent variable; SE: Huber-White standard errors. Note: All variables were standardized before model initiation.

While the models were statistically significant with respect to sustaining a non-contact time-loss injury, the average absolute probability of sustaining these injuries was .0011 in the combined EWMA model and .0012 in the ACWR model. These values correspond to 1.1 and 1.2 non-contact time-loss injuries per 1000 AEs. For the team-specific datasets, the EWMA and ACWR models for Team 1 both had an average probability of .0009. The Team 2 specific dataset had an average of .0012 for EWMA and .0013 for ACWR. Average injury probabilities by model and phase of year are compiled in Table 3.9. Additionally, observations with calculated injury probabilities greater than .04 ranged from 1 to 9 depending on the model and dataset. These frequencies represent .015% to .052% of the observations. Detailed injury probability frequencies by model and dataset are provided in Table 3.10.

Table 3. 9. Average injury probabilities by model, dataset, and phase of year.

Injury Probability Mean (± Std. Dev)	**Summer Conditioning**	**Pre-Season Practice**	**In-Season**	**Combined**
Combined EWMA	.0003 (± .0009)	.0013 (± .0021)	.0014 (± .0032)	.0011 (± .0027)
Combined ACWR	.0004 (± .0008)	.0013 (± .0023)	.0014 (± .0030)	.0012 (± .0026)
EWMA - Team 1	.0001 (± .0004)	.0017 (± .0030)	.0011 (± .0027)	.0009 (± .0024)
EWMA – Team 2	.0005 (± .0012)	.0011 (± .0020)	.0015 (± .0032)	.0012 (± .0028)
ACWR – Team 1	.0001 (± .0003)	.0017 (± .0032)	.0011 (± .0024)	.0009 (± .0022)
ACWR – Team 2	.0006 (± .0012)	.0014 (± .0025)	.0015 (± .0033)	.0013 (± .0030)

Table 3. 10. Frequency of injury probabilities by model and dataset.

Average Injury Probability	Combined EWMA	Combined ACWR	Team 1 EWMA	Team 1 ACWR	Team 2 EWMA	Team 2 ACWR
< 0.0050	16,992	16,540	6,428	6,416	10,523	10,114
0.0050 – 0.0099	557	503	152	85	428	385
0.0100 – 0.0149	154	146	47	75	115	123
0.0150 – 0.0199	70	71	29	24	51	44
0.0200 – 0.0249	31	27	9	4	28	17
0.0250 – 0.0299	16	11	4	2	12	6
0.0300 – 0.0349	10	6	1	2	5	6
0.0350 – 0.0399	3	6	2	1	5	5
> 0.0400	9	7	1	1	2	8
Average	.0011	.0012	.0001	.0001	.0012	.0013
Maximum	.0578	.0688	.0430	.0477	.0478	.0679

Figures 3.3 and 3.4 demonstrate the injury probability for each observation with an associated activity and a 7-day cumulative load greater than zero by previous 7-day workload (Figure 3.3) and workload ratio value (Figure 3.4). Additionally, descriptive statistics by phase of year are provided in Supplemental Table 3.3.

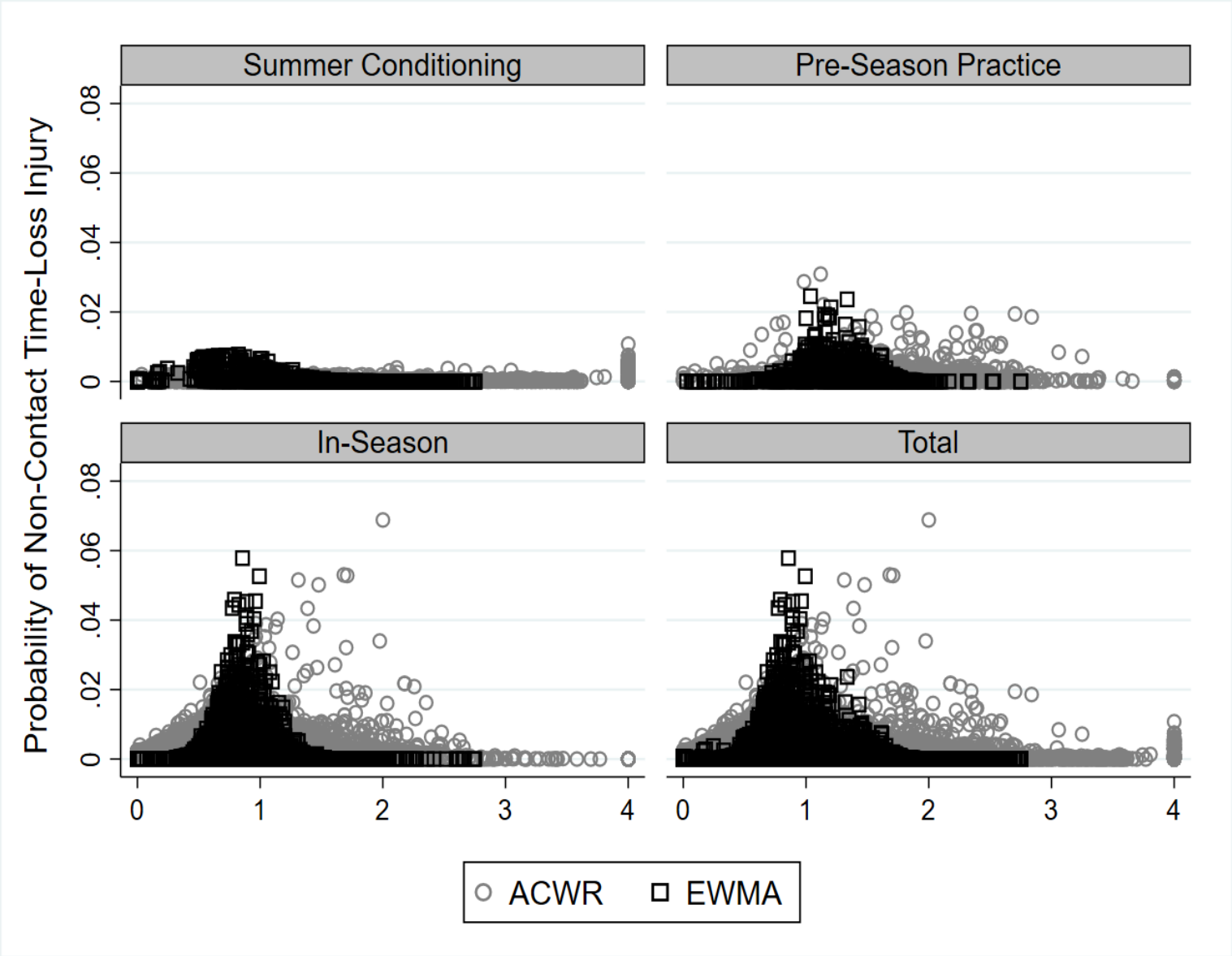

Figure 3. 3. Injury probability by workload ratio and phase of year

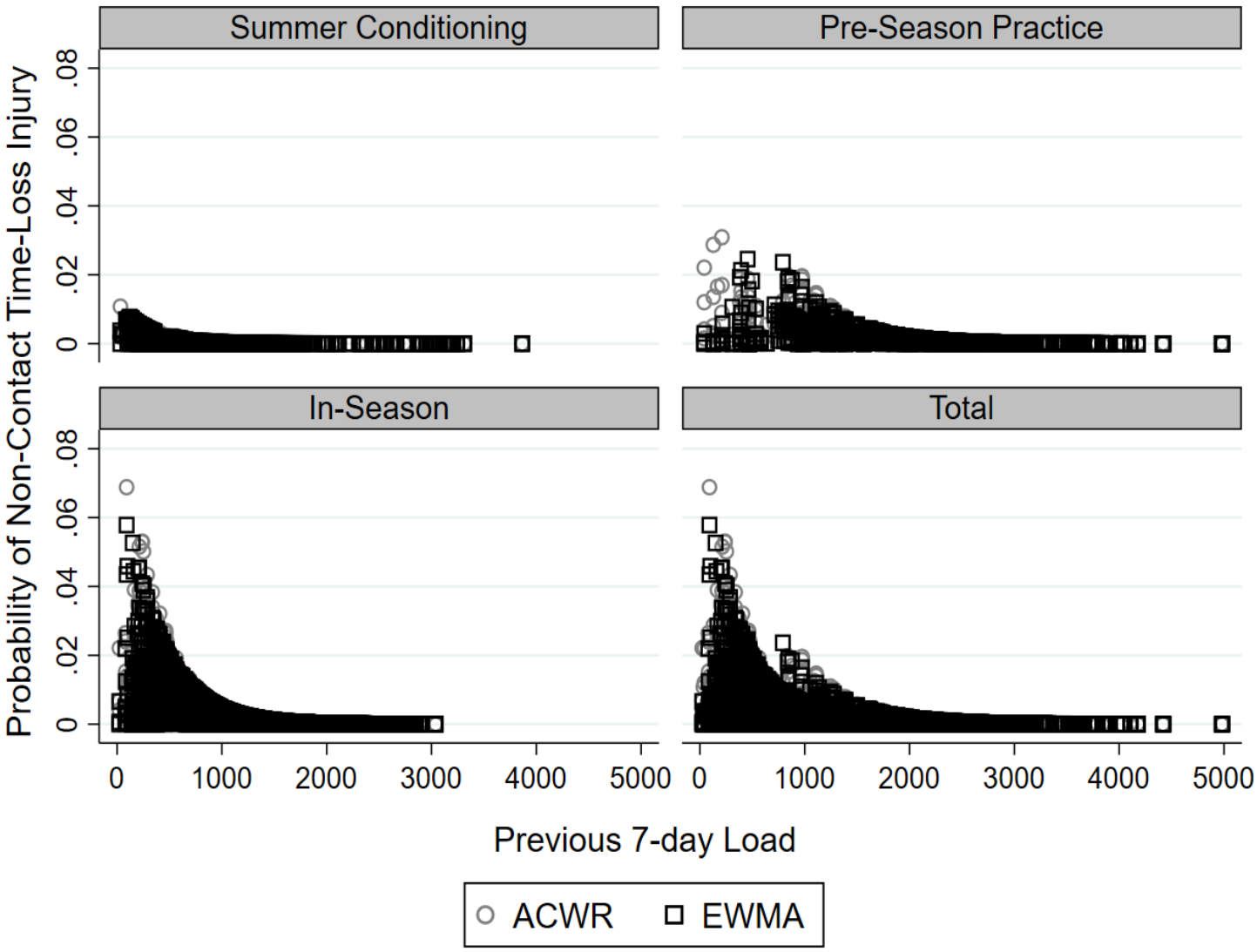

Figure 3. 4. Injury probability by previous 7-day load and phase of year.

Model comparison was performed for each team using ROC (Table 3.11) and Precision-Recall (P-R) area under the curve analyses (Table 3.12). For each team, the ROC area under the curve analysis failed to reject the null hypothesis that all four models were equivalent (Team 1: *p*-value = 0.2093; Team 2: *p*-value = 0.1632). ROC areas, standard errors confidence intervals, χ^2 statistics for each model and team are presented in Table 3.11. ROC curves are also displayed in Figure 3.5. Team 1 post-hoc power analysis with an effect size (w) of 0.5, $\alpha = .05$, sample size of 42, and 3 degrees of freedom yielded a power of 0.78. Team 2 post-hoc power with the same parameters and a sample size of 78 yielded a power of 0.97. P-R area under the curve analysis suggests that the team-specific models perform slightly better than combined models. However, the area under the curve for each model is small (< .0237) and thus indicate poor precision and recall.

Table 3. 11. ROC area analysis by team and model.

Team	Model	ROC Area	Standard Error	95% CI
Team 1	**Combined EWMA**	0.8773	.0687	.7426 – 1.000
	EWMA - Team 1	0.8715	.0740	.7266 – 1.000
	Combined ACWR	0.8444	.0817	.6843 – 1.000
	ACWR – Team 1	0.8513	.0843	.6861 – 1.000
	H_0: All models are equivalent | $\chi^2 = 4.53$ | Prob > $\chi^2 = 0.2093$			
Team 2	**Combined EWMA**	0.8652	.0493	.7686 – .9618
	EWMA - Team 2	0.8667	.0481	.7723 – .9611
	Combined ACWR	0.8304	.0631	.7067 – .9541
	ACWR – Team 2	0.8273	.0649	.7002 – .9545
	H_0: All models are equivalent | $\chi^2 = 5.12$ | Prob > $\chi^2 = 0.1632$			

Abbreviations: ROC, receiver operating characteristic; 95% CI, 95% confidence interval of asymptotic normal.

Table 3. 12. Precision-Recall area under the curve by team and model.

	Combined EWMA	Team EWMA	Combined ACWR	Team ACWR
Team 1	.0106	.0152	.0070	.0104
Team 2	.0143	.0143	.0210	.0237

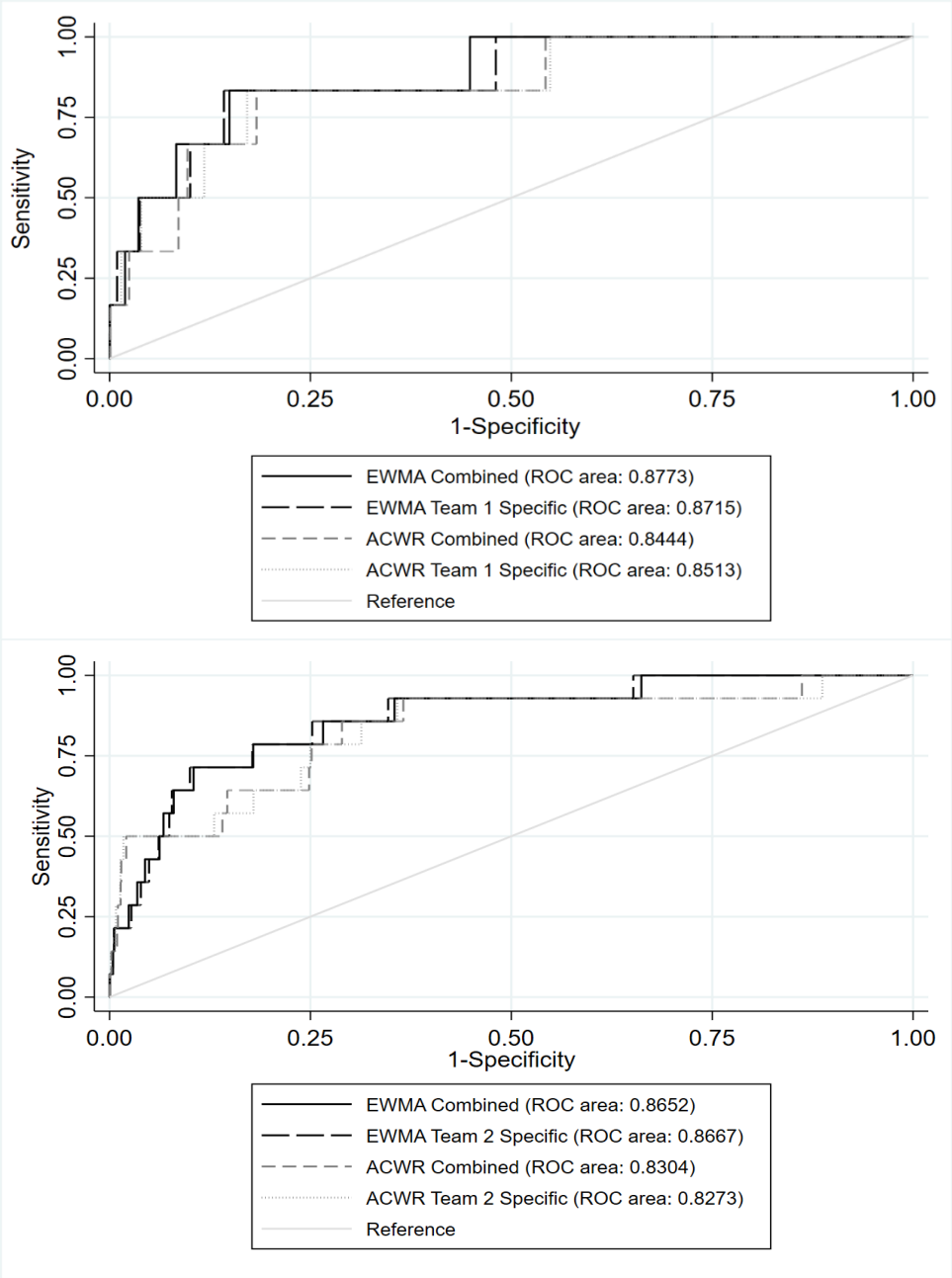

Figure 3. 5. ROC curves by team and model.

DISCUSSION

This is the first study to assess workload, workload ratios, and non-contact injury across multiple teams and years in collegiate football. The aims of this study were to compare the relationship between workload and workload ratios in collegiate football and to determine the association between workload ratio calculations and non-contact time-loss injury. Over the two-year investigation period assessing the summer conditioning, pre-season practice, and in-season competition phases, there were 44 (23 time-loss) non-contact injuries observed for each team. The results from this study indicate that weekly load and both ACWR and EWMA workload ratio calculations are significantly associated with non-contact time-loss injuries. Each of the 4 models calculated for each team, however, demonstrated an inverted-U relationship with injury probability when workload ratios were increased. This implies that increasing workload ratios beyond certain values, depending on the model, results in a decreased injury probability. In addition, increased weekly loads were associated with decreased probability of injuries. Together these findings suggest that these metrics may not be as associated with non-contact injury as previous reported. ROC and P-R assessment suggested that the team-specific models performed no better than combined models, and that all the models were extremely limited in prediction ability. The findings of this study provide evidence that monitoring workload ratios and weekly loads in isolation may not be integral to reducing injury risk in collegiate football.

While the two teams in this study each reported 44 non-contact injuries, the difference in the number of time-loss injuries between the two teams was substantial (Team 1: 6; Team 2: 17). The main time periods for which the difference in these results can be attributed are the 2018 pre-season (Team 1: 0; Team 2: 4) and in-season phases (Team 1: 1; Team 2: 6). It is

worth noting that Team 2 had more wearable devices (56) and more athletes (78) than Team 1 (28 and 42, respectively), and that this may have also contributed to the difference in the observed injury counts. However, the average activity exposure per athlete on Team 2 during the combined periods in question was 118.6, compared to only 103.3 for athletes on Team 1. This injury discrepancy is also reflected in the IRRs between the two teams for both the pre-season (Team 1: 2.98 AEs; Team 2: 3.68 AEs) and in-season (Team 1: 0.53 AEs; Team 2: 1.07 AEs) periods. While this data may suggest a more injurious environment for athletes on Team 2, the discrepancy in time-loss injuries may instead be due to the respective medical staff for each team operating under different sport participation guidelines. To the knowledge of the authors, consensus regarding the continued participation of injured athletes, modified or otherwise, in conditioning, practice, or competition sessions is limited to only a few of the many injuries these athletes may sustain. Future research across multiple teams and medical providers should seek to standardize the criteria for removal from sport participation. The combined non-contact time-loss IRR for the pre-season of 3.41 per 1000 AEs, falls within the 95% confidence interval reported by a previous 4-year study involving one collegiate football team (2.473 AEs; 95% CI: 1.663-3.548) (138). In addition, the combined pre-season and in-season IRR of 1.22 AEs in this study is lower than the reported 1.748 AEs (95% CI: 1.370-2.199) previously reported(138).

In collegiate football, most athletes report for summer conditioning after having a month away from the team medical and strength & conditioning staffs. Depending on the fitness status of these athletes when they return for summer conditioning, there exists the potential for exposure to larger increases in running volume and speed then what their current fitness status can handle. Previous research has suggested that sudden spikes in training load, which may occur at the onset of the summer conditioning phase, may lead to overtraining syndrome and

subsequent injury(224). The summer conditioning period had an overall non-contact injury rate of 6.95 AEs. However, the IRR for time-loss injury was 0.58 AEs. Team 1 reported no time-loss injuries in the summer conditioning period, while Team 2 reported 2 time-loss injuries. The discrepancy in IRRs may be attributed to the ability for practitioners to modify or alter summer conditioning sessions around particular injuries, and thus allow athletes to remain in the training session. For example, an athlete with a hamstring strain may run at a lower intensity than their peers. This modification would result in the athlete still being counted as having participated in the session. While this modification would be possible for this phase of training, such a modification would not be possible in practice or competition.

Prior research has suggested the monitoring, and subsequent modification, of sport participation exposure as an integral tool to mitigate injuries(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 189, 190, 195, 196, 198, 203, 207, 217, 218, 223). The limited research in college football has also suggested that the best model associated with non-contact injuries is the 7-day acute load to 21-day uncorrelated chronic load method which utilizes exponentially weighted moving averages (188). The results from this present study, however, dispute that this model is superior to the 7-day acute load to 28-day correlated chronic load model first proposed by Hulin, et al.(114).

The conflicting results from the present study may be due to several factors. The first is that this study, unlike previous college football research(188), utilized data from two teams over a two-year period. This diverse dataset may have improved the model estimations. Previous research also combined time-loss and non-time non-contact injuries for their model estimation. Previous research also included non-contact injuries to the upper-body and neck regions. A second factor may be the tool used to calculate workload, and therefore workload ratio. Previous

research had found positive medium- to large-sized correlations between both ACWR and EWMA workload ratios and non-contact injuries(4). However, this study utilized the internal load measure known as 'Session Rating of Perceived Exertion' (sRPE) as the measure to derive ACWR and EWMA ratio values, rather than the external load measure used in our study. This study also observed soccer players rather than American football players. While internal load ratios may be correlated with non-contact injury, our study demonstrated no relationship with the objectively measured external load metric. The discrepancy of the included injuries and the tool used to calculate workload likely contributed to the conflicting results.

Another factor contributing to the conflicting results may also be the statistical model used for the assessment of each variable to injury. The present study included not only the previous 7-day load as a covariate, but also a quadratic workload ratio term. Previous research had assessed the relationship of several variables including workload, workload ratios, to injury in isolation(102, 155, 188). The QIC results from the present study, however, indicated in each dataset, the multi-variate model utilizing a combination of these variables and a quadratic workload ratio term was an improvement over the univariate models of previous research. These findings are conceptually sound because relying purely on the univariate relationship can be misleading. For example, workload ratios address the relative change of an acute period to a chronic period. Therefore, an absolute increase of 500AU would yield a range of workload values depending on the chronic load. Assuming a chronic load value of 500AU, an increase from 500AU to 1000AU would yield a ratio value 2.0. Meanwhile, if the chronic load were 2000AU, the same 500AU increase would yield a workload ratio of 1.25. As was demonstrated in this study with lower QIC scores, absolute values should be included in injury models to provide better results.

This study, similar to previous research(48, 49, 59, 61, 65, 81, 107, 108, 114, 115, 125, 126, 148, 150, 157, 168, 169, 186, 219, 227), found a relationship between workload, workload ratios, and injury. However, this study demonstrated an inverted-U association between increasing workload ratio values and the probability of sustaining a non-contact injury, whereas previous research had demonstrated a U-relationship. Furthermore, the largest values of weekly load and workload ratios yielded no greater association to injury than lower values. These findings may be the result using continuous GEE method to analyze these variables rather than discretizing each into a series of bins as in previous research(28, 116, 188, 189). It has been noted in the literature(36) that discrete models were inferior to continuous models for assessing injury risk. The fact that the results from this study differ from those of previous research demonstrates the need for future research to apply continuous model techniques.

While there were no significant differences between the models regardless of workload ratio calculation method or the dataset used, the resulting P-R analysis did yield important insights. P-R area under the curve for these models indicated both low precision, calculated as the proportion of detecting true positives (non-contact time-loss injuries) to total detected positives (true positives + false positives), and recall, the proportion of detecting true positives to all positives (true positives + false negatives) in the data. These findings indicate the inability of these models to predict injury or be used as a diagnostic tool. Additionally, for practitioners interested in using workload ratios to help guide their decision making, the results of this study demonstrated that the absolute probability of injury rarely exceeded .04, otherwise stated as a 4% injury probability, in any of the four possible models. Even though this value is larger than the presented average injury probability, which was between .0001 to .0013 (.01% to 1.3%) depending on the model, the potential positive adaptations may outweigh this relatively low risk

of injury. Currently, practitioners should not rely solely on these models when designing training plans for optimal sport performance or rehabilitation.

Potential Strength & Limitations

The present study in college football possesses several strengths to further expand the knowledge on the association between workload, workload ratios, and non-contact injuries. First, the combination of daily observations over several years and the inclusion of a second team yields more generalizable results than previous studies. Second, the GEE model approach made it possible to assess these variables of interest despite having an unbalanced dataset, which is when athletes are unequally observed over time, non-normality, relatively few injury outcomes, and likely intercorrelated observations. Finally, this study analyzed workload and workload ratios continuously, as recommended by previous research(36), in order to limit the potential for false model discovery or rejection. Despite these advantages, this study does have its limitations. GEE statistical analysis addresses the overall population-level association between independent and dependent variables, and therefore is not ideally tuned to making predictions for the specific subjects observed within the dataset (60). In addition, this utilized the injury cataloging methods from previous research conducted by the sport's governing body (133). Though beneficial for historical comparisons, this catalog did not subcategorize the hip/thigh region into its major muscle groups, and as a result limits the comparisons of past research to future research for certain injuries, such as hamstring strains. Furthermore, this study only observed a subsection of each football team due to the limited number of wearable devices. The lack of full-team injury and workload data could impact the outcomes calculated by the models. Finally, this data was assessed retrospectively which did not permit a mutual injury classification and sport

participation criteria to be used by the two teams. As demonstrated in the data, there was a difference in the number of time-loss injuries disclosed by the teams which may be the result of the underlying decision-making process of each team. Future research should address these limitations in order to provide greater utility to practitioners.

Conclusions

Our study confirmed that although EWMA and ACWR workload ratio models were significantly associated with non-contact time-loss injuries, there was no significant difference between any of the four models used for each team. Additionally, all models demonstrated an inverted-U relationship between workload ratios and injury probability, suggesting that as workload and workload ratios increase beyond a point, injury probability decreases. Finally, while this study has added to the understanding of the interaction between workload, workload ratios, and non-contact injury, future research should seek to observe, and potentially include, other variables related to injury. For more generalizable findings to be uncovered, practitioners, teams, sporting bodies, and medical organizations should seek to not only create a multi-team database, but also outline a consensus regarding injury classification and sport participation status. The results provided in this study have the potential for practical implications into the training and injury management of college football players, with the goal to improve athlete overall health and success.

APPENDIX

Table 3. 13. Cumulative observations and activities by time of year and category.

	All Time Periods			2018			2019		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Observations	37,332	13,662	23,670	18,795	6,827	11,968	18,537	6,835	11,702
Activities	18,909	6,859	12,050	9,178	3,080	6,098	9,731	3,779	5,952
Football	14,354	4,699	23,670	6,958	2,072	4,886	7,396	2,627	4,769
Conditioning	4,555	2,160	2,395	2,220	1,008	1,212	2,335	1,152	1,183
	2018: Summer			**2018: Fall Camp**			**2018: Season**		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Observations	4,908	2,632	4,290	1,648	644	1,004	10,225	3,551	6,674
Activities	2,014	1,008	1,006	1,393	532	861	5,771	1,540	4,231
Football	0	0	0	1,393	532	861	5,565	1540	4,025
Conditioning	2,014	1,008	1,006	0	0	0	206	0	206
	2019: Summer			**2019: Fall Camp**			**2019: Season**		
	Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
Observations	6,597	2,577	4,020	1,620	644	976	10,320	3,614	6,706
Activities	2,063	1,036	1,027	1,245	476	769	6,423	2,267	4,156
Football	0	0	0	1,245	476	769	6,103	2,151	3,952
Conditioning	2,015	1,036	979	0	0	0	320	116	204

Table 3. 14. Non-contact (time-loss and non-time-loss) injury incidence rate ratios (IRR) by year and phase of season.

IRR (Time-Loss IRR)		Per 1000 Hours			Per 1000 Sessions		
		Total	**Team 1**	**Team 2**	**Total**	**Team 1**	**Team 2**
2018	**Combined**	3.39 (0.83)	5.24 (0.23)	2.58 (1.09)	5.34 (1.31)	7.47 (0.32)	4.26 (1.80)
	Summer	8.89 (0.64)	6.55 (0.00)	10.37 (1.04)	6.95 (0.50)	3.97 (0.00)	9.94 (0.99)
	Camp	5.58 (1.39)	8.37 (0.00)	4.18 (2.09)	11.49 (2.87)	15.04 (0.00)	9.29 (4.65)
	Season	1.90 (0.70)	3.90 (0.35)	1.11 (0.83)	3.29 (1.21)	7.14 (0.65)	1.89 (1.42)
2019	**Combined**	2.66 (0.68)	4.36 (0.83)	1.83 (0.61)	4.01 (1.03)	5.56 (1.06)	3.02 (1.01)
	Summer	5.32 (0.53)	9.10 (0.00)	3.28 (0.82)	4.85 (0.48)	5.79 (0.00)	3.89 (0.97)
	Camp	3.94 (1.97)	7.40 (3.70)	2.32 (1.16)	8.03 (4.02)	12.61 (6.30)	5.20 (2.60)
	Season	1.85 (0.39)	2.69 (0.30)	1.45 (0.43)	2.96 (0.62)	3.97 (0.44)	2.41 (0.72)
ALL	**Combined**	3.02 (0.79)	4.78 (0.65)	2.21 (0.85)	4.65 (1.22)	6.41 (0.87)	3.65 (1.41)
	Summer	6.95 (0.58)	7.87 (0.00)	6.41 (0.92)	5.96 (0.50)	4.89 (0.00)	6.89 (0.98)
	Camp	4.81 (1.67)	7.93 (1.70)	3.30 (1.65)	9.86 (3.41)	13.89 (2.98)	7.36 (3.68)
	Season	1.87 (0.54)	3.24 (0.32)	1.28 (0.64)	3.12 (0.90)	5.25 (0.53)	2.15 (1.07)

Table 3. 15. Kruskal-Wallis H test and Dunn's pairwise comparison for phase of year differences.

Dataset	**Workload**			**ACWR**			**EWMA**		
	X^2	**Deg.**	***p*-value**	**X^2**	**Deg.**	***p*-value**	**X^2**	**Deg.**	***p*-value**
Overall	12736.460	2	< .005	3643.707	2	< .005	3321.212	2	< .005
Team 1 – Specific	4674.514	2	< .005	1171.860	2	< .005	947.799	2	< .005
Team 2 – Specific	8533.410	2	< .005	2654.935	2	< .005	2424.037	2	< .005
Pairwise Comparison	**Summer : Pre-Season**	**Summer : Season**	**Pre-season : Season**	**Summer : Pre-Season**	**Summer : Season**	**Pre-season : Season**	**Summer : Pre-Season**	**Summer : Season**	**Pre-season : Season**
Combined	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005
Team 1 - Specific	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005
Team 2 – Specific	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005	< .005

Abbreviation: Deg, degrees of freedom in chi-square test. Note: Dunn's pairwise comparison test used a Bonferroni correction for multiple comparisons.

Table 3. 16. QIC results for linear and quadratic GEE models.

Model	Variables	P	Trace	QIC
Combined EWMA	EWMA, Weekly Load, Team	4	3.433	442.969
	$EWMA^2$, EWMA, Weekly Load, Team	**5**	**5.201**	**358.360**
	EWMA, Weekly $Load^2$, Weekly Load, Team	5	4.40	446.991
Combined ACWR	ACWR & Weekly Load, Team	4	3.483	379.693
	$ACWR^2$, ACWR, Weekly Load, Team	**5**	**5.657**	**356.733**
	ACWR, Weekly $Load^2$, Weekly Load, Team	5	4.346	384.530
Team 1 EWMA	EWMA & Weekly Load	3	2.599	414.339
	$EWMA^2$, EWMA, Weekly Load	**4**	**4.277**	**349.946**
	EWMA, Weekly $Load^2$, Weekly Load	4	3.547	432.307
Team 1 ACWR	ACWR & Weekly Load	3	2.801	388.811
	$ACWR^2$, ACWR, Weekly Load	**4**	**4.708**	**374.607**
	ACWR, Weekly $Load^2$, Weekly Load	4	3.691	406.367
Team 2 EWMA	EWMA & Weekly Load	3	2.329	459.879
	$EWMA^2$, EWMA, Weekly Load	**4**	**4.107**	**384.005**
	EWMA, Weekly $Load^2$, Weekly Load	4	3.282	460.308
Team 2 ACWR	ACWR & Weekly Load	3	2.289	388.818
	$ACWR^2$, ACWR, Weekly Load	**4**	**3.990**	**369.831**
	ACWR, Weekly $Load^2$, Weekly Load	4	3.055	388.350

Abbreviation: P, number of parameters including dependent variable. Note: All variables were standardized by phase of year before model initiation.

Table 3. 17. GEE Wald $\chi 2$ results and p-values by model and phase of year.

Phase of Year	Combined EWMA	Combined ACWR	Team 1 EWMA	Team 1 ACWR	Team 2 EWMA	Team 2 ACWR
Combined	42.40 < 0.005	32.49 < 0.005	10.37 0.016	19.35 < 0.005	27.38 < 0.005	17.75 < 0.005
Summer	832.47 < 0.005	528.65 < 0.005	Non-Convergence	Non-Convergence	97.82 < 0.005	1624.20 < 0.005
Pre-Season	8.36 0.039	13.75 < 0.005	7.54 0.057	12.77 0.005	15.23 < 0.005	19.95 < 0.005
In-Season	19.23 < 0.005	19.52 < 0.005	721.37 < 0.005	482.34 < 0.005	28.71 < 0.005	27.76 < 0.005

CHAPTER 4

A MULTI-YEAR ASSESSMENT OF EXTERNAL WORKLOAD AND INJURY RATES IN NCAA AMERICAN COLLEGE FOOTBALL

ABSTRACT

Quantifying NCAA Division 1 American football athlete demands using wearable devices has been utilized recently to assess workload and non-contact injury associations. Though studies have found associations between sudden increases and decreases in workload with subsequent injury, these studies have not investigated these associations beyond the pre-season and in-season periods. **PURPOSE:** To examine the association between workload ratios and non-contact injury-risk in American football for each component of the training cycle, and to compare the model fit between the exponentially weighted moving average (EWMA) and traditional acute:chronic workload ratio (ACWR) model. **METHODS:** Movement, non-contact, and overuse injury data from one American football team (n = 88) over three years were collected. Generalized estimating equation (GEE) models were developed for both the ACWR and EWMA workload ratio calculations. Previous 7-day cumulative workload (arbitrary units; AU) and workload ratio variables were standardized by phase of year and then tested for model fit. Best fitting models were determined by quasilikelihood under the independence model criterion (QIC), with the lowest scoring models chosen for statistical analysis. GEE results were presented as odds ratios and injury probabilities. These models were assessed by using area under the curve for both Receiver Operating Characteristic (ROC) and Precision-Recall curves. **RESULTS:** Sixty-seven injuries (36 time-loss) were observed with 26 (10 time-loss) occurring during winter conditioning, spring practice, and summer conditioning phases. Sites most often injured were the hip (Total 29; Time-Loss: 10), foot (13;7), and the knee (32;12). Strains were the most frequent diagnosis (32;12) followed by sprains (23;15). The overall injury incidence

rate ratio (IRR) per 1000 activity sessions (AEs) was 3.39 for all non-contact injuries and 1.80 AEs for time-loss injuries. Pre-season practice (Total: 7.05 AEs; Time-Loss: 4.70 AEs), summer conditioning (6.62 AEs; 1.42 AEs), and winter conditioning (4.73 AEs; 2.84 AEs) had the highest IRRs. Pre-season practice (2370 AU), in-season (1580 AU), and spring practice (1010 AU) phases had the largest weekly workloads. Summer conditioning (EWMA: 1.38; ACWR: 1.80), pre-season (1.27; 1.70), and spring practice (1.26;1.28) phases had the largest average workload ratios. The GEE model with the lowest QIC score included covariates for the previous 7-day cumulative load and the quadratic of the workload ratio. Models were significantly associated with non-contact time-loss injuries ($p < 0.005$). However, increased weekly load and the quadratic term of each workload ratio variable were associated with lower odds of injury. The average probability of sustaining and injury was .0016 in both models. Increased weekly load was associated with a lower probability of injury across each phase of the year. Workload ratio values displayed an inverted-U relationship with injury probability. The largest probability of injury value observed was 0.07 for the ACWR model, and 0.03 for the EWMA model. ROC and Precision-Recall curves revealed that ACWR and EWMA workload ratio calculation methods were indistinguishable in performance. **CONCLUSION:** While EWMA and ACWR workload ratio models were associated with non-contact time-loss injuries, the inverted-U relationship suggests that use of these variables in isolation may not be an adequate instrument to effectively reduce injury probability in college football.

INTRODUCTION

The 29,000 athletes who participate each year in elite-level college football(5) are invariably exposed to the potential for injuries as part of their normal training(133, 137, 158, 225, 229). Injury incidence rates have reportedly ranged from 3.17 to 4.90 per 1,000 athlete exposures(225). In addition, time-loss injury rates have been calculated to 24 per 10,000 football snaps(158). These injuries have been cited as major contributors in overall athlete health and team success(69, 87, 123). Therefore, assessing the environments in which these injuries occur is a prudent endeavor. Quantifying workload has become an increasingly popular component of such assessments. There are several methods to calculate workload, including subjective and device-based measures. Many practitioners have turned to the use of wearable deices for workload assessment due to greater objectivity in the values provided.

Wearable devices have been developed which utilize global position systems, accelerometers, a gyroscope, and a magnetometer to measure and quantify athlete movements (workload) during conditioning, practices, and games. Measuring workload has become a tremendously popular endeavor with numerous variables used in its assessment including both distance- and accelerometer-derived measures (102, 155). Practitioners have used these measures to compare current and past training demands(102, 155). Commonly, workload has been categorized into acute (recent 3 to 7 days) and chronic (previous 3 to 4 weeks) values. These values are combined to form a ratio value, which is then used assess the rate of workload change during training. Different mathematical approaches have been used to calculate this ratio(102, 155). The two commonly used measures are the 7-day acute to 28-day chronic method which uses rolling weekly averages (ACWR) (114), and 7-day acute to 21-day chronic method with exponentially weighted moving averages (EWMA) (102, 155, 228). Several studies

have found associations between both steep increases and decreases in workload, measured using workload ratios, with subsequent injury(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 189, 190, 195, 196, 198, 203, 207, 217, 218, 223). These prior studies examined the pre-season and in-season phases for numerous sports such as rugby(70, 217, 218), Australian rules football(48, 108), futsal(17, 164, 165), basketball(3, 110), volleyball(207), American football(188) and found these associations between workload ratios and increased risk of injury as well.

In college football, the 7:21-day coupled acute:chronic workload ratio calculated using an exponentially weighted moving average (EWMA) with a 3-day injury lag period demonstrated the greatest association to injury during the pre-season and in-season periods(188). While useful, these studies do not address the totality of American football sport participation which includes off-season conditioning, pre-season camp, and in-season phases of sport. Furthermore, previous research has been criticized for utilizing suboptimal statistical analyses(36, 216). In addition, American football studies are limited in quantity, the length of the observational timeframe, and the number of athletes observed. Longer studies with more athletes, thus larger data sets, will improve the generalizability of the results by minimizing the impact of individual and time effects in the data(154). Therefore, the purposes of this study were 1) To examine the association between workload ratios and non-contact injury-risk in American football for each phase within the annual calendar; and 2) To compare the model fit between the exponentially weighted moving average (EWMA) and traditional acute:chronic workload ratio (ACWR) model. We hypothesized that high workload ratios will be significantly associated with increased non-contact time-loss injury, with the EWMA model possessing greater association with injury than the traditional ACWR model.

METHODS

Participants

Data were collected from college football players (n=88) from a single NCAA Division 1 varsity team (mean ± SD: age: 20.8 ± 1.3 years, mass: 106.2 ± 19.7 kg, and height: 187.5 ± 5.9 cm). This cohort consisted of 30 skill players (wide receivers & defensive backs), 30 big skill players (running backs, tight ends, and linebackers), and 28 power players (offensive and defensive linemen). A yearly comparison of these positions is reported in Supplemental Table 4.1. Quarterbacks and specialists were not included in this study due to their unique practice environments. Due to the roster size being greater than the number of available units, players most likely to play in games, as determined by the coaching staff, were assigned units to wear. All players trained full-time during their participation with the team. The observational period began on July 13th, 2017 and ran continuously through December 29th, 2019. This period captured the 2017, 2018, and 2019 football seasons. These data were collected retrospectively, and all participant workload and injury data were de-identified. All experimental procedures for this study were approved by the Michigan State University Human Research Protection Program.

Quantifying Workload

Workloads were collected from wearable global positioning system (GPS) devices (Optimeye S5, Catapult Innovations, Melbourne, AUS). These devices combine a 10Hz GPS with a 100 Hz tri-axial accelerometer, a gyroscope, and a magnetometer to derive an external workload metric known as ‘player load’ (Catapult Innovations). Previous research established the reliability, construct validity, convergent validity of the components and algorithms within

the wearable devices with both ground-based and standardized treadmill running (13, 57, 58, 100, 127, 132, 161, 183, 209, 214).

These devices were worn between the scapulae of the players in compression vests during all conditioning sessions and non-padded football practices, which was dictated by the coaching staff. These vests came in varying sizes from small to xxxx-large to ensure a secure, comfortable fit. During padded practices, players wore the devices in boxes mounted on their shoulder pads in the same location as their garments. Players wore the same device during every conditioning and practice session. Following each session, the data were downloaded into the accompanying software (Openfield, Catapult Innovations, Melbourne, AUS). This software calculated workload as the sum of all accelerometer movements in the three-dimensional plane. This is a unit-less quantification as is defined by the manufacturer as:

$$\text{Player/Body Load} = \sqrt{\frac{(\alpha_{y1} - \alpha_{y-1}) + (\alpha_x - \alpha_{x-1}) + (\alpha_z - \alpha_{z-1})}{100}}$$

Where, y refers to the forward/backward acceleration, x refers to lateral acceleration, and z refers to vertical acceleration. Workload ratios were calculated using both the traditional acute:chronic workload ratio (ACWR) and the exponentially weighted moving average (EWMA) version. The ACWR was calculated by dividing the most recent 7-day accumulated workload by the average weekly workload between the most recent week and the three preceding weeks(114).

The exponentially weighted moving average (EWMA) was calculated daily for both acute (past 7 days) and chronic (previous 21 days) workloads. The first activity was arbitrarily entered as the starting chronic value consistent with the method proposed by previous research(188). The equation used to calculate the acute period was:

$$\textit{Acute: } EWMA_t = \left[Load_t * \left(\frac{2}{7+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{7+1}\right)\right] * EWMA_{t-1}\right\}$$

The equation used to calculate the chronic period was:

$$\textit{Chronic: } EWMA_t = \left[Load_t * \left(\frac{2}{21+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{21+1}\right)\right] * EWMA_{t-1}\right\}$$

The variable 'Load' in this instance refers to the accelerometer-derived Player Load, subscript t refers to the current observation, and subscript *t*-1 refers to the previous observation.

The acute period as divided by the chronic to give a ratio value for each day. In the event of missing data, the activity average for the position group was used for that individual.

Definition of Exposure

An athlete exposure was defined as one athlete participating in one activity. Activities were comprised of conditioning, practice, and competition sessions. Each athlete's participation and duration was recorded by the accompanying software for the wearable devices. All participations and durations were confirmed by the team's practitioners.

Definition of Injury

All injuries that occurred during the study period were diagnosed and classified by the team's sports medicine staff. Injury data collected were categorized based on the NCAA Sports Injury Surveillance program(133). Lower-body and trunk injuries classified as non-contact or overuse in mechanism were combined under the term non-contact and included in the analyses, as both could occur due to improper activity rate increases(87, 94). Time-loss was defined as

any injury where an athlete was unable to participate in subsequent conditioning, practice, or competition sessions.

Statistical Analyses

All calculations and analyses utilized the Stata IC v16.1 software package (StataCorp LLC, College Station, TX). Injury incidence rate ratios (IRRs) were determined by dividing the total number of non-contact and overuse injuries by the exposure time and reported, with 95% confidence intervals, as both rates per 1000 activity hours (HEs) and per 1000 activity sessions (AEs). Daily calculations of 7-day cumulative load (weekly load), ACWR, and EWMA ratio values were made for each athlete. Kolmogorov-Smirnov tests for normality were conducted for the 7-day cumulative load, ACWR, and EWMA ratio values. These results indicate non-normal distributions for each variable. Generalized estimating equation (GEE) models with Huber-White standard errors were used to account for non-normality, a sparse number of injury occurrences, as well as probable intercorrelation between observations for each athlete. Athletes served as the repeated-measures unit and each day served as the observation unit. The binary outcome variable was specified to be a new non-contact injury occurrence. Because the outcome variable (non-contact time-loss injury) is binary (injured or not), a logit-link function with a binomial error structure was used. In addition, GEEs require a correlation matrix between observations be defined but not necessarily correct, so an exchangeable correlation matrix was used.

To compare the association between workload ratio values (EWMA and ACWR) with non-contact injury, two models were developed. Each model considered the weekly load in addition to the workload ratio to observe the effect of absolute acute load. Both the workload

ratio and weekly load variables were standardized by subtracting the mean value of the variable and dividing by its standard deviation in order for the GEE to perform optimally. These variables were standardized by each phase of the year. For example, the variables observed during winter conditioning were standardized to all winter conditioning variables. In accordance with suggestions by previous research, both linear-only and quadratic functions of each variable were combined in a GEE (36, 139). Unlike prior research, where observations were made weekly and as such required a lag on the dependent injury occurrence (139, 188), observations in this study were made daily so a lagged dependent injury outcome was not used. Because of the daily observations, only days with an activity occurring were used in the analyses. These analyses were also restricted to observations where the weekly load was greater than zero. A zero weekly load would indicate a currently injured athlete and would have corresponding workload ratio which would never be associated with a new injury. The quasilikelihood under the independence model criterion (QIC) was then used to compare the linear and quadratic variations of each standardized variable in each model(60). QIC is an extension of Akaike information criterion (AIC), and as such the model with the lowest corresponding QIC is generally deemed the best fit(60). Statistical analyses were represented by odds ratios (OR), Huber-White standard errors (SE), 95% confidence intervals (CIs), and with a statistical significance value set at $p < .05$. The EWMA and ACWR models were compared using Receiver Operating Characteristic (ROC) curves and Precision-Recall (P-R) curves. While both ROC and P-R curves assess the diagnostic ability of these models to detect injury occurrences (positive outcomes), ROC curves assess each model's ability to detect true injury occurrences in relation to true non-injury (negative outcomes), while P-R curves assess each model's ability to correctly identify true injuries and are unconcerned with detecting true non-injury. The

imbalance in outcomes contained in this study makes P-R curves are particularly useful. By assessing the area under the curves (AUC) for each of these models we can determine how well these models separate injuries from non-injuries. The model with the larger AUC is the model that is better at detecting true injury status

Power Analysis

We desired 80% power to detect a difference of at least moderate effect size (ES = 0.5) between GEE models. Therefore, with the α level set at $\alpha = .05$ and 1 degree of freedom, a sample size of 32 players was required and was associated with a critical χ^2 value of 3.841. However, due to the unbalanced data set, we chose to include all observed athletes for each year (2017: 44; 2018: 58; 2019: 56), thus ensuring at least 32 players were always observed.

RESULTS

Total Observations, Injury Frequency, and Injury Rates

There were 40,367 total observation days recorded spanning 898 days (mean ± SD: 458.7 ± 282.3 days per player). Days with activities accounted for 18,861 of the total observation days. Activities were categorized as either conditioning, practice, or competitive games. Cumulative observations by category, time of year, and duration are presented in Table 4.1. Highlighted in Table 4.2 is also the unequal observation and activity counts from 2017 to 2018. This is due to the team acquiring more wearable devices between these years.

Table 4. 1. Cumulative observations and activities by time of year.

Activity Type	Total	2017	2018	2019
Observations	40367	6822	17179	16366
All Activities	18953	4265	7582	7103
Practice	13168	3414	5107	4696
Games	1894	557	659	678
Conditioning	3799	294	1776	1729
Activity Duration (1000 Hours)	**Total**	**2017**	**2018**	**2019**
All Activities	33.09	8.73	12.20	12.16
Practice	24.17	6.65	8.87	8.65
Games	4.26	1.58	1.37	1.30
Conditioning	4.66	0.50	1.96	2.20

During the observation period, 67 total non-contact/overuse injuries, impacting 776 activity sessions, were recorded for the 88 athletes being tracked. Of these 67 injuries, 36 resulted in time loss from participation (587 activities). The three sites most often injured, both

overall and time-loss, were the hip/thigh (Total: 29; Time-Loss: 10), foot (Total: 13; Time-Loss: 9), and knee (Total: 12; Time-Loss: 7) regions. While strains were the most frequent injury diagnosis (Total: 32; Time-Loss: 12), more time-loss injuries occurred from sprains (Total: 23; Time-Loss: 15). Further categorization of injury site, mechanism, and frequency can be found in Table 4.2.

Table 4. 2. Injury site, mechanism, and frequency by year.

Injury Site	**Total [Time-Loss]**	**2017**	**2018**	**2019**
Total	67 [36]	10 [8]	31 [15]	26 [13]
Trunk	3 [3]	1 [1]	2 [2]	0 [0]
Hip/Thigh	30 [10]	4 [4]	16 [4]	10 [2]
Knee	12 [7]	2 [2]	3 [1]	7 [4]
Lower Leg	4 [4]	0 [0]	2 [2]	2 [2]
Ankle	4 [2]	0 [0]	1 [0]	3 [2]
Foot	13 [9]	3 [1]	6 [5]	4 [3]
Other	1 [1]	0 [0]	1 [1]	0 [0]
Injury Diagnosis	**Total [Time-Loss]**	**2017**	**2018**	**2019**
Total	67 [36]	10 [8]	31 [15]	26 [13]
Fracture	3 [3]	0 [0]	2 [2]	1 [1]
Sprain	23 [15]	5 [3]	7 [4]	11 [8]
Strain	32 [12]	4 [4]	17 [5]	11 [3]
Other	9 [6]	1 [1]	5 [4]	3 [1]

The overall injury rate observed was 3.55 AEs (2.02 HEs), while the time-loss injury rate was 1.91 AEs (1.09 HEs). The hip/thigh, foot, and knee regions had IRRs (time-loss) of 1.59 (0.53), 0.69 (0.48), and 0.64 (0.37) respectively. A complete summary of IRRs by site and diagnosis can be found in Table 4.3.

Table 4. 3. Injury incidence rate ratios (IRRs) with 95% confidence intervals by site and mechanism.

	Injury Rates per 1000 Athlete Exposures		**Injury Rates per 1000 Hours**	
Injury Site	**All Injuries [95% CI]**	**Time-Loss [95% CI]**	**All Injuries [95% CI]**	**Time-Loss [95% CI]**
Total	3.55 [2.50, 4.60]	1.91 [1.81, 2.01]	2.02 [1.21, 2.84]	1.09 [0.91, 1.26]
Trunk	0.16 [0.00, 0.32]	0.16 [0.00, 0.32]	0.09 [0.00, 0.19]	0.09 [0.00, 0.19]
Hip/Thigh	1.59 [0.91, 2.27]	0.53 [0.16, 0.90]	0.91 [0.42, 1.39]	0.30 [0.14, 0.47]
Knee	0.64 [0.27, 1.00]	0.37 [0.12, 0.63]	0.36 [0.14, 0.58]	0.21 [0.07, 0.35]
Lower Leg	0.21 [0.03, 0.39]	0.21 [0.03, 0.39]	0.12 [0.01, 0.23]	0.12 [0.01, 0.23]
Ankle	0.21 [0.00, 0.46]	0.11 [0.00, 0.29]	0.12 [0.00, 0.26]	0.06 [0.00, 0.17]
Foot	0.69 [0.55, 0.82]	0.48 [0.23, 0.72]	0.39 [0.29, 0.49]	0.27 [0.10, 0.44]
Other	0.05 [0.00, 0.14]	0.05 [0.00, 0.14]	0.03 [0.00, 0.08]	0.03 [0.00, 0.08]
	Injury Rates per 1000 Athlete Exposures		**Injury Rates per 1000 Hours**	
Injury Diagnosis	**All Injuries [95% CI]**	**Time-Loss [95% CI]**	**All Injuries [95% CI]**	**Time-Loss [95% CI]**
Total	3.55 [2.50, 4.60]	1.91 [1.81, 2.01]	2.02 [1.21, 2.84]	1.09 [0.91, 1.26]
Fracture	0.16 [0.01, 0.31]	0.16 [0.01, 0.31]	0.09 [0.00, 0.18]	0.09 [0.00, 0.18]
Sprain	1.22 [0.87, 1.57]	0.80 [0.45, 1.14]	0.70 [0.48, 0.91]	0.45 [0.24, 0.66]
Strain	1.70 [0.94, 2.45]	0.64 [0.34, 0.93]	0.97 [0.44, 1.50]	0.36 [0.24, 0.49]
Other	0.48 [0.23, 0.72]	0.32 [0.09, 0.55]	0.27 [0.10, 0.44]	0.18 [0.03, 0.33]

Observations, Injury Frequency, and Injury Rates by time of year

The time of year that had the greatest number of injuries occur was the in-season period (Total: 22; Time-Loss: 14). However, the pre-season practice phase had the highest overall IRR (7.05 AEs; 3.24 HEs) and time-loss IRR (4.70 AEs; 2.16 HEs). Though the summer conditioning period had the second highest IRR by session (6.62 AEs), it had the highest IRR by duration (6.11 HEs). A full summary of injury occurrence and IRRs by time of year are in Table 4.4 and Table 4.5, respectively.

Table 4. 4. Injury site, frequency [time-loss], and mechanism by time of year.

Injury Site	Total [Time-Loss]	Winter Conditioning	Spring Practice	Summer Conditioning	Pre-Season Practice	In-Season
Combined	67 [36]	5 [3]	7 [4]	14 [3]	18 [12]	23 [14]
Trunk	3 [3]	1 [1]	0 [0]	1 [1]	1 [1]	0 [0]
Hip/Thigh	30 [10]	2 [0]	3 [0]	9 [1]	10 [6]	5 [3]
Knee	12 [7]	0 [0]	2 [2]	1 [0]	3 [3]	6 [2]
Lower Leg	4 [4]	0 [0]	1 [1]	1 [1]	0 [0]	2 [2]
Ankle	4 [2]	2 [2]	0 [0]	1 [0]	0 [0]	1 [0]
Foot	13 [9]	0 [0]	1 [1]	1 [0]	4 [2]	7 [6]
Other	1 [1]	0 [0]	0 [0]	0 [0]	0 [0]	1 [1]
Injury Diagnosis	**Total [Time-Loss]**	**Winter Conditioning**	**Spring Practice**	**Summer Conditioning**	**Pre-Season Practice**	**In-Season**
Combined	67 [36]	5 [3]	7 [4]	14 [3]	18 [12]	23 [14]
Fracture	3 [3]	0 [0]	1 [1]	0 [0]	1 [1]	1 [1]
Sprain	23 [15]	2 [2]	3 [3]	2 [0]	4 [3]	12 [7]
Strain	32 [12]	2 [0]	3 [0]	10 [2]	10 [6]	7 [4]
Other	9 [6]	1 [1]	0 [0]	2 [1]	3 [2]	3 [2]

Table 4. 5. Non-contact injury rates by time of year.

Injury Rates per 1000 Athlete Exposures			Injury Rates per 1000 Hours	
Time of year	**All Injuries [95% CI]**	**Time-Loss [95% CI]**	**All Injuries [95% CI]**	**Time-Loss [95% CI]**
Combined	3.55 [2.50, 4.60]	1.91 [1.81, 2.01]	2.02 [1.21, 2.84]	1.09 [0.91, 1.26]
Winter	4.73 [2.57, 6.88]	2.84 [1.16, 4.51]	2.65 [1.02, 4.29]	1.59 [0.89, 2.29]
Spring Practice	4.61 [1.23, 8.00]	2.64 [1.48, 3.80]	2.56 [1.41, 3.70]	1.46 [1.22, 1.70]
Summer	6.62 [0.94, 12.30]	1.42 [0.30, 2.54]	6.11 [0.00, 12.80]	1.31 [0.15, 2.47]
Pre-Season Camp	7.05 [6.36, 7.74]	4.70 [4.23, 5.16]	3.24 [2.81, 3.66]	2.16 [1.98, 2.34]
Season	2.03 [1.49, 2.58]	1.20 [0.90, 1.50]	1.15 [0.72, 1.58]	0.68 [0.47, 0.89]

Activity Loads and Workload Ratios

The pre-season practice phase was the time of year where athletes experienced the highest weekly workload (2370; 95% CI: 2340, 2400). This period was followed by in-season (1580; 95% CI: 1570, 1590) and spring phases (1010; 95% CI: 990, 1030). A full summary of average weekly loads by year and phase, with 95% confidence intervals, are in Table 4.6. Box plots of weekly load by phase are shown in Figure 4.1.

Table 4. 6. Average weekly load with 95% confidence intervals by year and phase of season.

Phase	All Years	2017	2018	2019
Winter Conditioning	560 [550, 570]	-	670 [650, 690]	470 [450, 490]
Spring Practice	1010 [990, 1030]	-	900 [870, 920]	1170 [1140, 1200]
Summer Conditioning	590 [570, 600]	830 [750, 910]	540 [520, 550]	600 [580, 630]
Pre-Season Camp	2370 [2340, 2400]	2370 [2310, 2430]	2290 [2230, 2340]	2460 [2410, 2500]
In-Season	1580 [1570, 1590]	1580 [1560, 1600]	1570 [1560, 1590]	1590 [1580, 1600]

Note: Workload values are rounded to the nearest ten's unit and have arbitrary units.

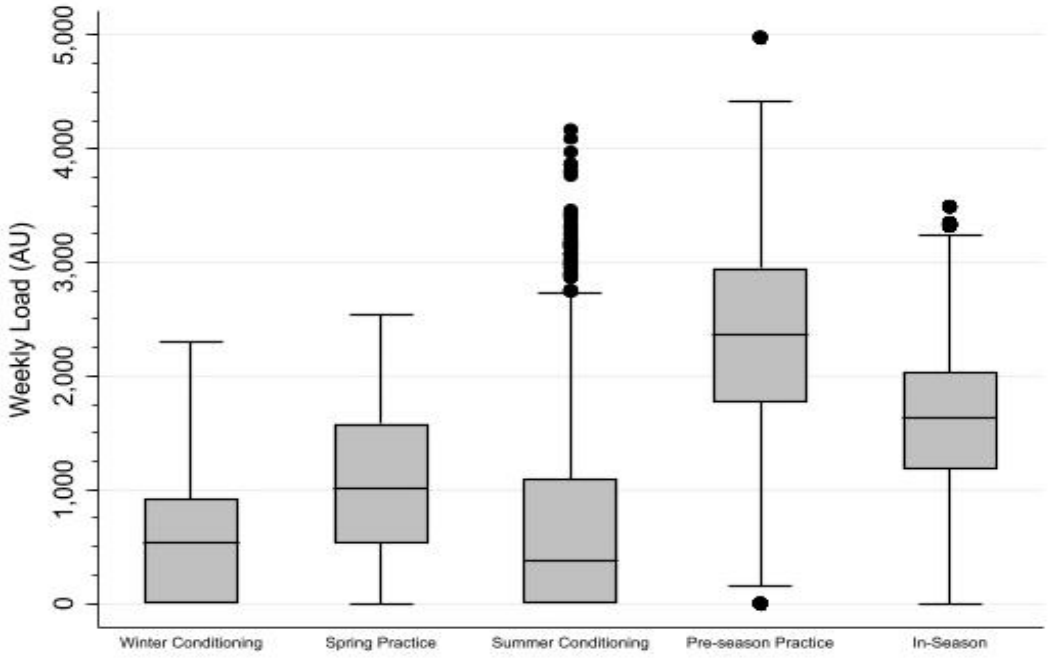

Figure 4. 1. Weekly load box plots by phase of season.

Average workload ratios also demonstrated variation throughout the calendar year. The overall average workload ratio calculated using EWMA was 1.13, and 1.23 when calculated using ACWR. The summer conditioning (EWMA: 1.38; ACWR: 1.80), pre-season (1.27; 1.70), and spring practice (1.26;1.28) phases had the largest average workload ratios. Combined and phase-specific average workload ratios with 95% confidence intervals are provided in Table 4.7.

Table 4. 7. Average workload ratio with 95% confidence intervals by phase of season.

EWMA	EWMA	ACWR
Combined	1.13 [1.13, 1.14]	1.23 [1.22, 1.24]
Winter Conditioning	1.10 [1.07, 1.13]	1.35 [1.31, 1.39]
Spring Practice	1.26 [1.24, 1.27]	1.28 [1.24, 1.27]
Summer Conditioning	1.38 [1.36, 1.40]	1.80 [1.74, 1.85]
Pre-Season Camp	1.27 [1.26, 1.28]	1.70 [1.67, 1.72]
In-Season	1.05 [1.04, 1.05]	1.03 [1.02, 1.04]

Note: values are rounded to the nearest hundredth's unit.

Weekly variations did occur for load, ACWR, and EWMA values within each phase of the season. Box plots for weekly load (Figure 4.2), EWMA (Figure 4.3), and ACWR values (Figure 4.3), comprised of uninjured athletes, for each phase of the season can be found below. The winter conditioning, spring practice, and summer conditioning periods all contain weeks where the athletes were on break from team activities. These were weeks where their activity was unobserved, and as a result are reflected as having no weekly load values and very low EWMA and ACWR values.

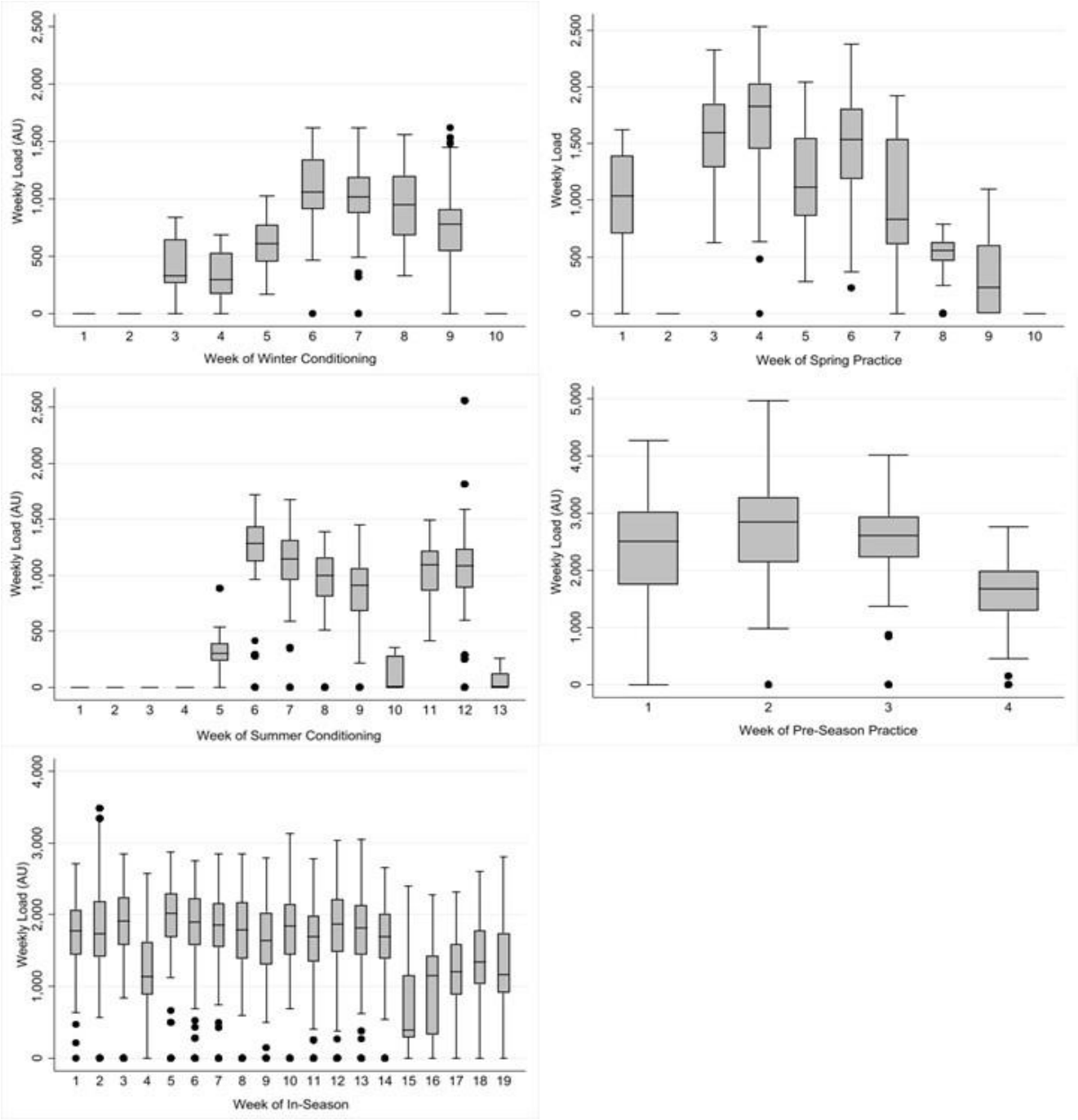

Figure 4. 2. Weekly load box plots by phase of season.

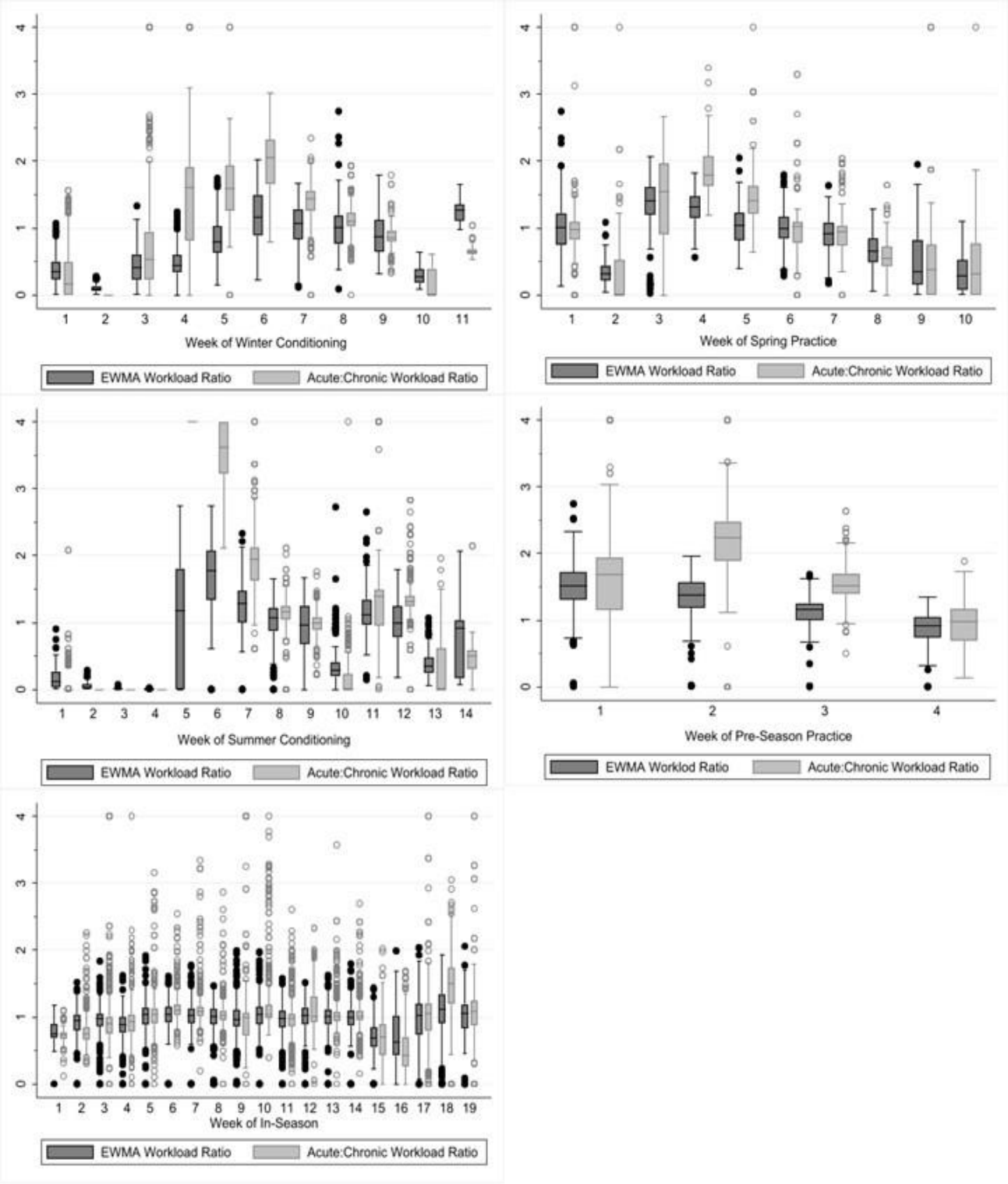

Figure 4. 3. Workload ratio box plots by phase of season.

Generalized Estimating Equation Models

In both EWMA and ACWR GEEs, including a quadratic workload ratio term was associated with a lower QIC value and was therefore chosen for further statistical analysis. Table 8 presents the total parameters, trace value, and QIC results for linear and polynomial versions of each model.

Table 4. 8. QIC results for GEE models for linear and quadratic covariates.

Model	Variables	P	Trace	QIC
EWMA	EWMA & Weekly Load	3	2.743	658.803
	$EWMA^2$, EWMA, Weekly Load	**4**	**4.570**	**565.151**
	EWMA, Weekly $Load^2$, Weekly Load	4	3.753	659.607
ACWR	ACWR & Weekly Load	3	2.655	566.061
	$ACWR^2$, ACWR, Weekly Load	**4**	**4.160**	**524.967**
	ACWR, Weekly $Load^2$, Weekly Load	4	3.442	565.276

Abbreviation: P, number of parameters including dependent variable; QIC: quasilikelihood information criterion statistic. Note: All variables were standardized by phase of year before model initiation. Models in bold were selected for further analysis.

Overall, both EWMA (Wald $\chi^2 = 51.14$, $p < 0.005$) and ACWR (Wald $\chi^2 = 40.84$, $p < 0.005$) models were statistically significant. Aside from the linear EWMA covariate, all workload ratio and weekly load variables had individual statistically significant associations with non-contact time-loss injury risk. Increased weekly load was associated with lower odds of injury in both the EWMA (OR: 0.20; CI: 0.10-0.40; $p < 0.005$) and the ACWR (OR: 0.14; CI: 0.07-0.27; $p < 0.005$) models. Each model maintained its statistical significance when each phase of the year was run in isolation (Supplemental Table 4.2). GEE results by variable are provided in Table 4.9.

Table 4. 9. GEE model results by variable.

EWMA Model	Odds Ratio	95% CI	SE	z-score	*p*-value
EWMA^2	0.52	0.28 – 0.97	0.16	-2.05	0.04
EWMA	1.22	0.57 – 2.59	0.47	0.51	0.608
Weekly Load	0.20	0.10 – 0.40	0.07	-4.54	< 0.005
ACWR Model	**Odds Ratio**	**95% CI**	**SE**	**z-score**	***p*-value**
ACWR^2	0.72	0.58 – 0.91	0.08	-2.82	0.005
ACWR	2.65	1.38 – 5.11	0.89	2.92	0.004
Weekly Load	0.14	0.07 – 0.27	0.05	-5.82	< 0.005

Abbreviations: 95% CI, 95% confidence interval number of parameters including dependent variable; SE: Huber-White standard errors. Note: All variables were standardized before model initiation.

While the models were statistically significant with respect to odds of injury, the mean absolute probability of sustaining an injury was .0016 in both the EWMA and ACWR models. This corresponds to 1.6 non-contact injuries every 1000 AEs. Injury probability frequencies are displayed in Table 4.10.

In both models, the period with the highest mean probability of injury was pre-season practice (EWMA: .0019; ACWR: .0021). Figures 4.4 and 4.5 demonstrate the injury probability for each observation with an associated activity and a 7-day cumulative load greater than zero by previous 7-day workload (Figure 4.4) and workload ratio value (Figure 4.5). Additionally, descriptive statistics by phase of year are provided in Supplemental Table 4.3.

Table 4. 10. Frequency of Injury Probabilities by Model.

Injury Probability Range	EWMA	ACWR
< 0.0050	16,380	15,100
0.0050 – 0.0099	813	814
0.0100 – 0.0149	270	207
0.0150 – 0.0199	98	89
0.0200 – 0.0249	35	35
0.0250 – 0.0299	9	14
0.0300 – 0.0349	1	11
0.0350 – 0.0399	0	6
> 0.0400	0	13
Maximum observed value	0.03287	0.07628

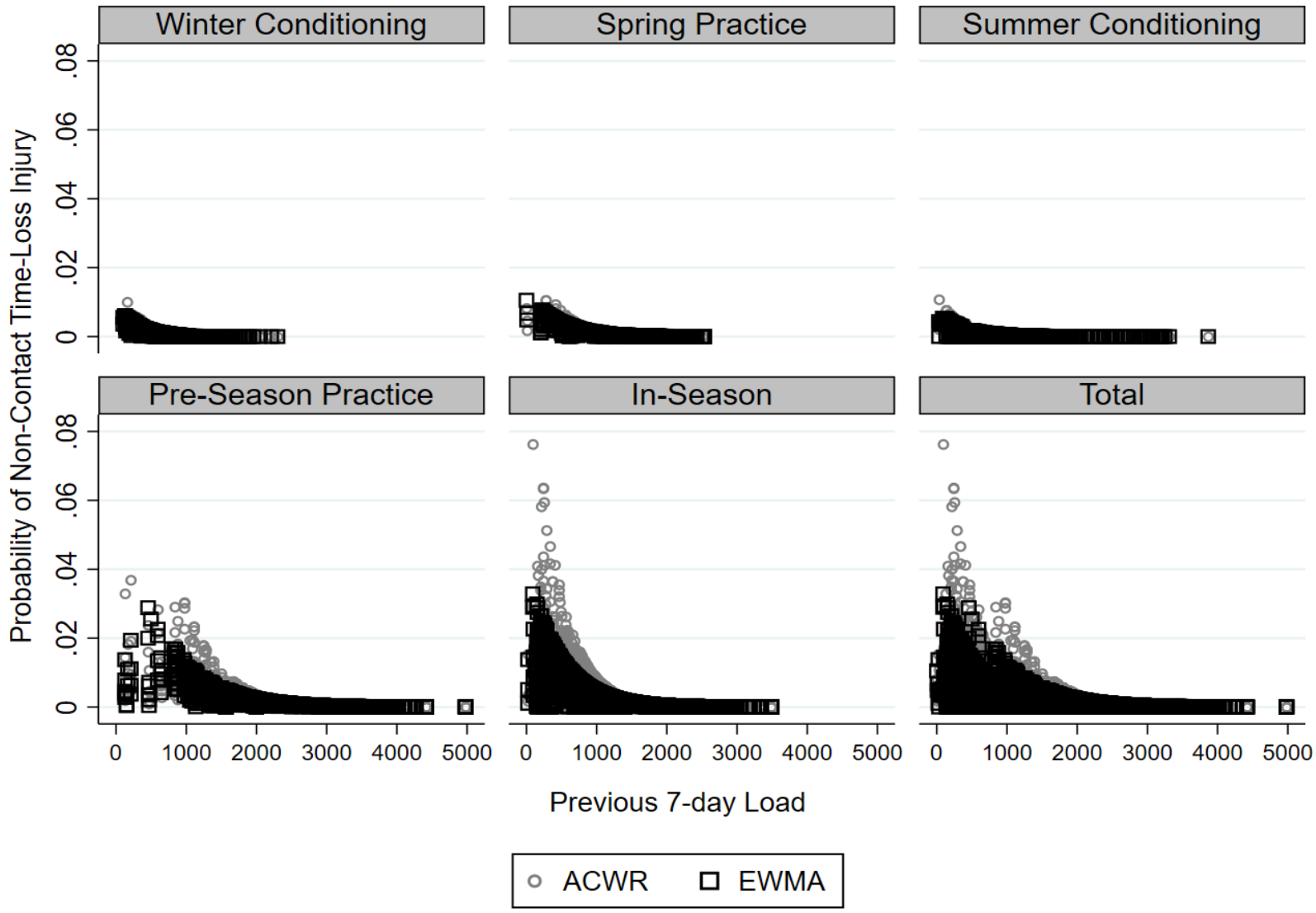

Figure 4. 4. Injury probability by previous 7-day load and phase of season.

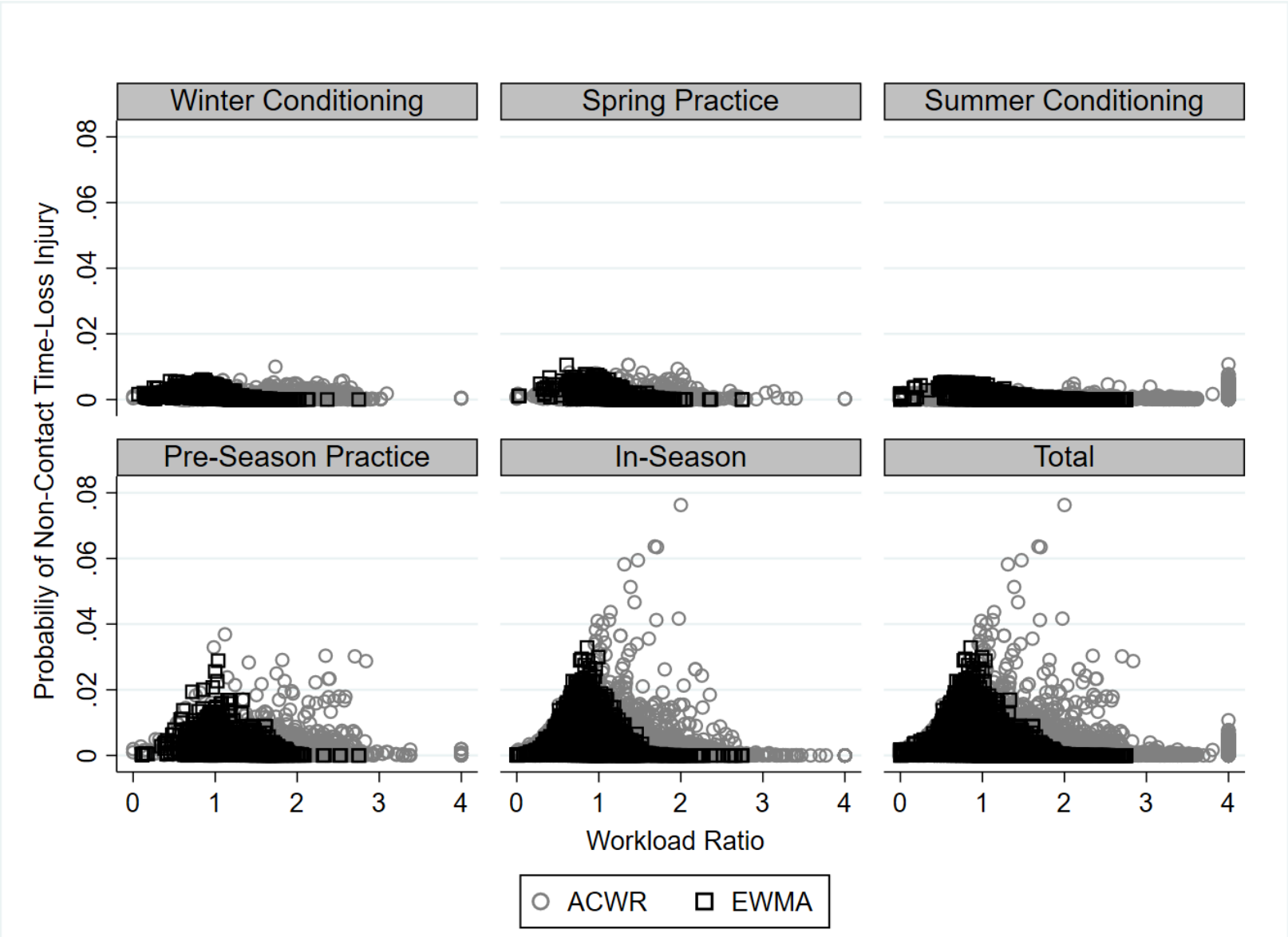

Figure 4. 5. Injury probability by workload ratio and phase of season.

Model comparison was performed using ROC (Figure 4.6) and Precision-Recall (PR) area under the curve analyses (Figure 4.7). ROC area under the curve analysis failed to reject the null hypothesis that the EWMA (Area: 0.83; CI: 0.77 – 0.89) and ACWR (Area: 0.83; CI: 0.76 – 0.90) models were equivalent ($\chi^2 = 0.01$, $p = 0.94$). PR area under the curve analysis (EWMA: 0.0110; ACWR: 0.0185) also suggested that both models were equivalent.

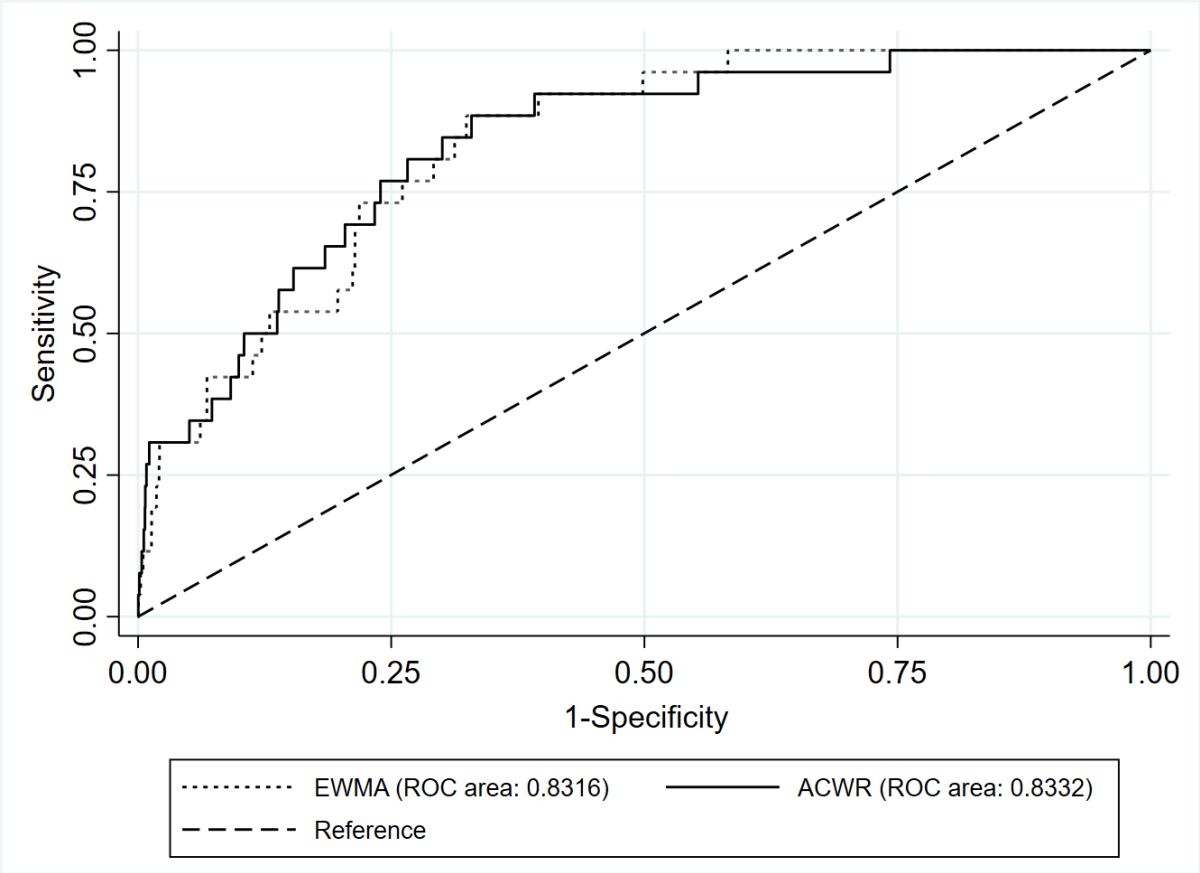

Figure 4. 6. ROC area under the curve chart comparing EWMA and ACWR models.

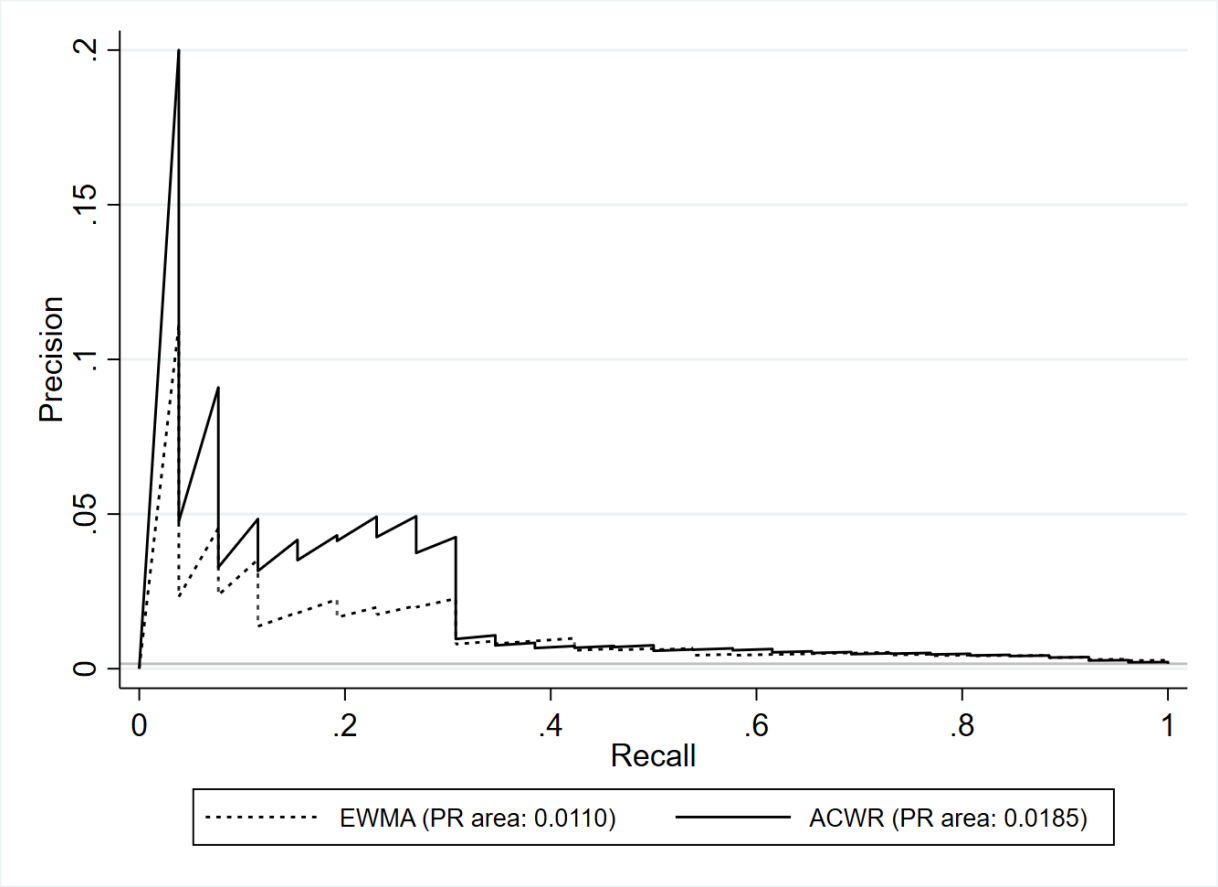

Figure 4. 7. Precision-Recall chart comparing EWMA and ACWR models.

DISCUSSION

This is the first study to investigate injury incidence rate ratios, workload, and workload ratios in college football over a multi-year period. It is also the first study to expand the evaluation these metrics to the winter conditioning, spring practice, and summer conditioning phases of sport participation. The aim of this study was to utilize a multi-year database to assess the relationship of workloads and workload ratios to non-contact injuries in Division 1 college football participation across an entire calendar year. Overall, the winter conditioning, spring practice, and summer conditioning phases combined for 26 of the 67 total observed non-contact injuries (38.8%). In addition, the results of this study indicate that both EWMA and ACWR workload ratios are significantly associated with non-contact time-loss injury. This study failed to demonstrate that one workload ratio calculation was superior to other in its association with non-contact injury. Additionally, increased workload ratios demonstrated an inverted-U relationship with injury probability, while increased weekly load demonstrated a negative relationship with injury probability. These relationships were maintained even when each phase of the year was observed in isolation. Furthermore, absolute injury probability was observed to be on average .0016 for both models, with the greatest injury probability observed to be .0329 for the EWMA model and .0763 for the ACWR mode. The findings of this study provide evidence that all phases of sport competition should be surveilled for injury, and that monitoring workload ratios and weekly loads alone may not be the key to reducing injury risk in collegiate football.

Previous injury surveillance research in college football was restricted to the pre-season practice and in-season time periods. As such, comparisons between this study and that research were also restricted to those time points. The pre-season practice IRR reported in this study

(4.70 AEs; 95% CI: 4.23 – 5.16) was significantly greater than the IRR reported in a prior 4-year study (2.47 AEs; 95% CI: 1.663 – 3.55) (138). However, the combined data from pre-season practice and in-season phases yielded an IRR of 1.87 per 1000 AEs, which was comparable to previous research (1.758 AEs; 95% CI: 1.37 – 2.20) (138). Future research should seek to standardize the format of data reporting and provide access to compiled data sets to provide more general IRRs.

This study demonstrated that non-contact injury occurrence is not restricted to the pre-season practice and in-season phases of sport participation. In totality, 39% of all non-contact injuries (n = 26) and 28% of time-loss injuries (n = 10) occurred between winter conditioning, spring practice, and summer conditioning phases. Furthermore, the IRRs of these phases were greater than the in-season phase. Additionally, the summer conditioning period had the highest IRR when expressed as injuries per 1000 hours. While these phases do not immediately precede, or include, competition, they are opportunities for practitioners to exert influence over training and recovery strategies in order to reduce a non-trivial number of non-contact injuries. Future research should examine the impact of injury mitigation during these phases of participation as well as the pre-season and in-season phases.

Previous studies have suggested the monitoring and adjustment of sport participation exposure as a means to mitigate injury occurrence(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 189, 190, 195, 196, 198, 203, 207, 217, 218, 223). Research in college football has even suggested that the model with the best association to non-contact injuries was the 7-day acute load to 21-day uncorrelated chronic load using exponentially weighted moving averages (188). The results from this study, however, dispute the assertion that this model is superior to the original 7-day acute load to 28-day correlated chronic load model proposed by Hulin and colleagues(114).

The contradictory results from this study may be the result of one or more factors in the study design. The first factor is that this study utilized a larger dataset than previous research in college football(188). Previous research in college football observed a single pre-season and in-season period, whereas this study was able to combine three years of data. Observing multiple years aids to mitigate the opportunity for outlier seasons to be viewed in isolation and then be reported as the sport norm. In addition to different lengths of observation, the differing results may also be due to a utilization inclusion of different injuries in the analysis. While previous research included all non-contact injuries, including upper body and neck injuries, this study restricted observations to those occurring in the trunk and lower limbs. Given the ground-based environment of college football, the authors in this study felt the inclusion of upper-body non-contact injuries was largely unrelated to running-based workload and workload ratio calculations and therefore ill-advised. Furthermore, the contradictory findings may also be the result of this study utilizing the previous 7-day cumulative load as a covariate. Research has previously observed workload, workload ratios, and several other variables in in isolation(102, 155, 188). The QIC results obtained in this study, however, suggested the inclusion of both a previous 7-day load covariate and a quadratic workload ratio term in the model. Relying solely on the workload ratio variable can be misleading without knowing the acute workload being observed. Workload ratio values are relative in that an arguably small load comparison of 200au acute to 100au chronic would yield the same ratio value (2.0) as a 2000au acute to 1000au chronic. The absolute values of these workload ratio components likely influence the association with injury occurrences, as was demonstrated in this study with lower QIC scores, and therefore should be included information in any practical setting.

Numerous studies have demonstrated that both workload and workload ratios are associated with injury(48, 49, 59, 61, 65, 81, 107, 108, 114, 115, 125, 126, 148, 150, 157, 168, 169, 186, 219, 227). This study is no exception. However, the results here demonstrated an inverted-U association between increasing workload ratio values and the probability of sustaining a non-contact injury. Whether observed in totality or within each phase of the year, the highest weekly workloads and workload ratios had no greater associated probability to injury than lower values. These findings may be the result of analyzing these variables in a continuous method rather than the discretization methods used in previous research(28, 116, 188, 189). While the results of this study did demonstrate an increase in injury probability as workload ratios increased to a certain point, the absolute probability of injury only exceeded .04 in the ACWR model 13 times, and never exceeded .04 in the EWMA model. For some practitioners and coaches, this absolute injury risk increase may be small enough to still warrant the planned training or competition stimulus.

Potential Strength & Limitations

The present study in college football utilized several advantages to expand the understanding of the relationship between workload, workload ratios, and non-contact injury occurrence. First, the accumulation of daily observations made over several years yielded a dataset that captured all phases of sport training and participation. Second, the GEE statistical approach carried out in this study made it possible to interpret the relationship of the variables of interest despite having an unbalanced dataset, which is when athletes are viewed unequally over time. Finally, this study was able to analyze workload and workload ratios continuously, as suggested by previous research(36), in order to limit the potential for false model discovery or

rejection. Despite these advantages, this study is not without its limitations. For starters, GEE statistical analysis, while being very valuable for these data, seeks to address the overall population-level association between independent and dependent variables, and therefore is not tuned to making predictions for the specific subjects observed within the dataset (60). This study utilized cataloging methods from previous research conducted by the sport's governing body. While useful for comparisons between studies, a main drawback of this catalog was that it did not subcategorize the hip/thigh region into its major muscle groups. This makes comparison of past research to future research for injuries of particular interest, such as hamstring strains, difficult. Furthermore, this study only observed athletes who were assigned wearable devices as determined by the coaching staff, and therefore most likely to play in games. There could be an unobserved underlying trait, skill, or strategy employed by these athletes or coaches which could contribute to them experiencing fewer non-contact injuries than what has been surveilled in previous research. Future research should seek to address these potential shortcomings.

Conclusions

This study was able to demonstrate that while EWMA and ACWR workload ratio models may be significantly associated with non-contact time-loss injuries, one model was not distinguishable from the other. Additionally, the models with the best fit for this data demonstrated an inverted-U relationship with injury, suggesting that as workload and workload ratios increase, there may not be an associated increase in injury probability. Finally, while this study has provided improved understanding of the relationships between the association between workload, workload ratios, and non-contact injury, future research should seek to observe additional covariates potentially related to injury such as strength, power, flexibility, fitness, etc.

This research into injury incidence rate ratios and workload has the potential for considerable implications for the training and management of college football players, with the objective to ultimately improve athlete health and success.

APPENDIX

Table 4. 11. Positional count comparison by year.

Unique IDs	Total	2017	2018	2019
All Athletes	88	44	58	56
Skill	30	14	20	19
Big Skill	30	12	19	18
Power	28	18	19	19

Table 4. 12. QIC results for GEE models by phase of year.

Model Variables	Phase of Year	Wald χ^2	*p*-value
EWMA^2, EWMA, Weekly Load	Combined	51.14	< 0.005
	Winter Conditioning	152.04	< 0.005
	Spring Practice	257.69	< 0.005
	Summer Conditioning	308.16	< 0.005
	Fall Camp	14.80	< 0.005
	In-Season	39.41	< 0.005
ACWR^2, ACWR, Weekly Load	Combined	40.84	< 0.005
	Winter Conditioning	35.97	< 0.005
	Spring Practice	31.67	< 0.005
	Summer Conditioning	811.08	< 0.005
	Fall Camp	8.88	0.031
	In-Season	42.78	< 0.005

Table 4. 13. Injury probability by model and phase of year.

EWMA Model	Mean	Median	SD	Min	Max
Combined	.0016	.0006	.0027	3.48e-11	.0329
Winter Conditioning	.0009	.0004	.0013	1.14e-09	.0061
Spring Practice	.0011	.0003	.0015	6.02e-08	.0106
Summer Conditioning	.0005	.0002	.0009	2.15e-07	.0053
Fall Camp	.0019	.0009	.0027	1.07e-07	.0289
In-season	.0018	.0007	.0030	3.48e-11	.0329
ACWR Model	**Mean**	**Median**	**SD**	**Min**	**Max**
Combined	.0016	.0005	.0032	1.34e-08	.0763
Winter Conditioning	.0010	.0006	0.0011	4.72e-07	.0100
Spring Practice	.0010	.0005	.0014	1.36e-05	.0106
Summer Conditioning	.0007	.0003	.0012	1.34e-08	.0107
Fall Camp	.0021	.0008	.0036	7.80e-06	.0369
In-season	.0018	.0006	.0036	3.38e-07	.0763

Abbreviations: SD: standard deviation; Min: minimum; Max: maximum.

Consent Forms

Research Participant Information and Consent Form

STUDY TITLE: A multi-year assessment of external workload and injuries in american football.

BRIEF SUMMARY

You are being asked to participate in a research study. Researchers are required to provide a consent form to inform you about the research study, to convey that participation is voluntary, to explain risks and benefits of participation including why you might or might not want to participate, and to empower you to make an informed decision. You should feel free to discuss and ask the researchers any questions you may have.

You are being asked to participate in a research study of football athlete workload and injury / illness occurrence from 7/13/2017 thru 1/10/2021. Your participation in this study is simply accessing your training and injury data. You will be asked to allow the athletic medicine team to report basic information about any injuries or illnesses you sustain during the course of the data collection period. Your participation is voluntary, and you may withdraw consent at any time during the data collection period.

The most likely risks of participating in this study are the standard risks associated with participation in collegiate football. The other risk of participating in this study is a data breach.

You will not directly benefit from your participation in this study. However, your participation in this study may contribute to the understanding how athletic participation increases are associated with increased injury and illness risk.

PURPOSE OF RESEARCH

The purpose of this research study is to investigate whether or not the rate of increased activity is a contributor to an increased risk of injury and illness. Understanding this relationship can allow for more appropriate practice planning and/or the potential for rule changes at the NCAA level.

WHAT YOU WILL BE ASKED TO DO

Allow the study team access to your Catapult monitoring data during the study time period (7/13/2017 thru 1/10/2021). In addition, you must allow the athletic medicine staff to report basic information on any injuries or illnesses you sustained or will sustain during the study period. This information will include injury/illness type, body location involved, whether it was received from contact during an activity, and any activity time missed or modified during the study duration. All personal information identifying you will be removed from the study.

POTENTIAL BENEFITS

You will not benefit personally from being in this study. However, we hope that in the future other people might benefit from this study because the data provided will help administrators and coaches design more optimal policies and training plans to minimize the risk of injury during the summer and fall camp training periods.

POTENTIAL RISKS

The major risk for participating in this study is a data breach. All injury data will be void of identifying information and your participation will be anonymous.

PRIVACY AND CONFIDENTIALITY

Participants will be assigned a unique study ID number, which will be used within all data files. The informed consent forms and identifying information will be stored separately from all collected data. All wearable and injury data will be stored on either password protected files within locked offices at the

Approved by a Michigan State University Institutional Review Board effective 1/11/2020.
This version supersedes all previous versions. MSU Study ID STUDY00003402.

Skandalaris Football Building, or online within the Catapult Sports web application. This application is HIPAA compliant and is part of the normal use of these devices prior to this study. The de-identified injury data will be stored in password protected files within the locked office of the study coordinator for three years. In addition, the data will be kept confidential to the maximum extent allowable by law. Identified injury data will be stored within athletic medicine's electronic medical records software as is current standard practice. All data will remain at Michigan State University and will not continue on with the study coordinator should they leave the university. Study findings will be reported in the aggregate form so that individual participants cannot be identified.

YOUR RIGHTS TO PARTICIPATE, SAY NO, OR WITHDRAW

You have the right to say no to participation in the research study. There will be no consequences if you decline and you will not be criticized. You will not lose any benefits that you normally receive.

COSTS AND COMPENSATION FOR BEING IN THE STUDY

There are no costs or compensation to you for being in the study.

RESEARCH RESULTS

A copy of the study will be provided to you should you request it.

FUTURE RESEARCH

Information that identifies you will be removed from the study results. This information includes name, age, and injury information that may make it possible to identify your involvement. Your de-identified information will not be reported on individually in the study. After personal identifiers are removed from the data, the information could be used for future research studies or distributed to another investigator for future research studies without additional informed consent from the subject or the legally authorized representative.

CONTACT INFORMATION

If you have concerns or questions about this study, such as scientific issues, how to do any part of it, or to report an injury, please contact the researcher Bill Burghardt at 771 Chestnut Rd, East Lansing, MI 48824 or email burghardt@ath.msu.edu or 517-927-7366. You may also contact the Principal Investigator, Dr. Karin Pfeiffer at 308 W. Circle Dr., Room 27R IM Sports Circle, East Lansing, MI 48824, kap@msu.edu, 517-353-5222.

If you have questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or e-mail irb@msu.edu or regular mail at 4000 Collins Rd, Suite 136, Lansing, MI 48910.

DOCUMENTATION OF INFORMED CONSENT

Your signature below means that you voluntarily agree to participate in this research study. You will be given a copy of this consent form to keep.

_____ _____

Signature Date

_____

Name

Approved by a Michigan State University Institutional Review Board effective 1/11/2020.
This version supersedes all previous versions. MSU Study ID STUDY00003402.

MSU AUTHORIZATION TO USE OR DISCLOSE
HEALTH INFORMATION FOR RESEARCH

Name: _____

Date of Birth: _____

If you sign this document, you give permission to all health care providers at the MSU HealthTeam to use or disclose (release) your health information that identifies you for the research study described below.

TITLE: A multi-year assessment of external workload and injuries in American football

PURPOSE OF RESEARCH:

The purpose of this research study is to investigate whether increased activity rates elicit an internal inflammatory response which subsequently increases the risk of non-contact injury or illness. Understanding this relationship can allow for more appropriate practice planning, mediating interventions, and/or the potential for rule changes at the NCAA level to minimize injury risk.

DESCRIPTION OF INFORMATION TO BE USED OR DISCLOSED (RELEASED) FOR THIS RESEARCH INCLUDES:

This study asks to collect basic injury description information from your medical records for the dates within the study collection period. This injury information will include mechanism of injury (i.e. contact, non-contact, chronic), diagnosis (i.e. contusion, concussion, dislocation, muscle/tendon strain), body part injured (i.e. knee, head, neck, arm/elbow, lower leg), and time-lost from sport participation. This study will also collect the Catapult Sport GPS movement data from the wearables you wearing during team activities. Your information will be anonymized and there will be no data published in the study on you as an individual. All data will be reported on by position and/or the compiled team data.

THE HEALTH INFORMATION LISTED ABOVE MAY BE USED AND/OR DISCLOSED (RELEASED) TO:

William Burghardt (Study Coordinator), Dr. Karin Pfeiffer (Primary Investigator), the Michigan State University Human Research Protection Program

You may refuse to sign this authorization and your refusal will not affect your ability to obtain treatment, however, it may affect your ability to participate in this research study.

V17-01 (12-3-2017)

MSU AUTHORIZATION TO USE OR DISCLOSE
HEALTH INFORMATION FOR RESEARCH

You may change your mind and revoke (take back) this Authorization at any time, except to the extent that MSU HealthTeam has already acted based on this Authorization. To revoke this Authorization, you must write to: The MSU privacy officer at Michigan State University, 965 Fee Road, A130 East Fee Hall, East Lansing, MI 48824.

MSU HealthTeam is required by law to protect your health information. By signing this document, you authorize MSU HealthTeam to use and/or disclose (release) your health information for this research. Those persons who receive your health information may not be required by Federal privacy laws (such as the Privacy Rule) to protect it and may share your information with others without your permission, if permitted by laws governing them.

EXPIRATION: Your Authorization to disclose the above information expires at the end of the research study.

_____

Signature of individual participant or personal representative Date

_____

Printed name of individual participant or personal representative

_____

If applicable, a description of personal representative's authority to act for the individual participant

YOU WILL BE PROVIDED A COPY OF THE SIGNED FORM

A COPY OF THE SIGNED FORM MUST BE PROVIDED TO MSU HEALTHTEAM

V17-01 (12-3-2017)

CHAPTER 5

C-REACTIVE PROTEIN, EXTERNAL WORKLOAD, AND NON-CONTACT INJURY RATES IN NCAA AMERICAN FOOTBALL PLAYERS

ABSTRACT

Current research indicates that rapid increases in workload predisposes athletes to greater injury risk. This research has generally failed to provide a mechanism for these injuries and has ignored the value of assessing inflammatory markers as a secondary data source. **PURPOSE:** To assess the relationships among rate of external workload increase, C-reactive protein (CRP) levels, and non-contact injuries during American football training and participation. **METHODS:** Daily external workloads, injury information, and weekly salivary C-reactive protein (CRP) levels were collected for 19 American football players from the same NCAA Division 1 team for 12 weeks. Injury rates per 1000 athlete-exposures (AEs) and per 1000 hour-exposures (HEs) were calculated. Both traditional 7-28 day acute:chronic workload ratios (ACWR) and 7:21 exponentially weighted moving average acute:chronic workload ratios (EWMA) were calculated daily. **RESULTS:** Eighteen injuries (15.04 AEs; 9.07 HEs) were observed, with 3 being a result of a non-contact mechanism (2.51 AEs; 1.51 HEs) and 1 resulting in time-loss from sport (0.84 AEs; 0.50 HEs). These 3 injuries were muscle strains to the hip/thigh region. One-way repeated measures ANOVA determined CRP did not vary across time ($F_{11,176} = 1.41$; $p = 0.17$). Average weekly load was 1837 $\pm$ 791 arbitrary units (AU). Load was determined to vary across time ($F_{11,192} = 3.97$; $p < 0.001$). Change in CRP was poorly correlated to change in load from week to week (r = 0.15). Average EWMA and ACWR values were 0.99 $\pm$ 0.33 and 1.17 $\pm$ 0.61, respectively. CRP was poorly correlated with EWMA and ACWR ratio values (r = -0.11; -0.07). Panel regressions determined that weekly load ($p = 0.49$), ACWR ($p =$

0.93), and EWMA (p = 0.21) values were individually not associated with CRP concentrations.

CONCLUSION: Results failed to demonstrate that increases in workload or workload ratios were associated with increases in CRP concentration and subsequent non-contact injury risk. In addition, the observed muscle strains did not result in subsequent increases in CRP concentrations.

INTRODUCTION

Current National Collegiate Athletic Association (NCAA) policies may expose American football players to increased injury risk. These policies effect approximately 29,000 football players at the NCAA Division 1 level each year(5). The pre-season period for college football occurs in August and is approximately four weeks in length(6). Prior to this period, college football players spend eight weeks weight training and conditioning for their sport. The NCAA limits all weight training and conditioning activities to a combined eight hours per week during this period. The pre-season period in August allows for 20 hours per week of practice and weight training sessions. These policies indicate a strong probability that athletes experience at least a 2.5-fold increase in workload during this transition.

Recently, studies in football(188, 189) and other sports(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 190, 195, 196, 198, 203, 207, 217, 218, 223) have suggested that this increased rate of workload accumulation as athletes progress from conditioning to practice may be a contributor to non-contact injuries such as muscle strains, ligament sprains, and stress fractures. Injuries resulting in lost participation time are often cited as major contributors in overall team success(69, 87, 123). To reduce injury risk and optimize individual performance, teams have begun monitoring athlete workloads using external wearable devices that utilize global positioning systems (GPS) with built-in accelerometers and gyroscopes. These devices have been used in numerous studies involving team sports such as rugby(59, 68, 115, 116), soccer(83, 125, 149, 150), and Australian rules football(68, 167-169, 204). The workload values obtained by these devices can be categorized into acute (most recent 7 days) and chronic (previous 3- to 4-weeks) values, though the specific days associated with each value vary. These values can be referenced as a ratio, which are then used to measure the rate of increase or decrease in an

athlete's current training relative to their training history. The value for this ratio has been calculated using various mathematical approaches(102, 155). The two most common methods for quantifying this ratio are the original 7-day acute to 28-day chronic method which utilizes rolling averages (Traditional ACWR) (114), and the 7-day acute to 21-day chronic method with exponentially weighted moving averages (EWMA) (102, 155, 228). This research has shown associations with non-contact and overuse injury occurrence when athletes increase their weekly (acute) activity at rates greater than 1.5 times their recent (chronic) exposure(48, 65, 108, 167-169, 186, 189). In college football, the 7:21-day coupled ACWR calculated using an exponentially weighted moving average (EWMA) with a 3-day injury lag period demonstrated the greatest association with injury during the pre-season and in-season periods(188).

To the authors' knowledge, however, these research studies have not proposed an injury mechanism or provide a framework through which to explain the association between high acute:chronic workload ratios and increased injury risk. Following a training, practice, or competition session, athletes will experience both fitness and fatigue effects(11). Fitness effects may often include increased muscle size, strength, recruitment patterns, oxygen consumption efficiency, mitochondrial density, blood supply, etc.(45). Fatigue effects, by contrast, are impairments to performance resulting from a depletion in energy substrate availability(56, 105, 205, 236), such as muscle glycogen depletion, or from increased inflammation leading to soreness and edema(68, 191). The severity and duration of these effects largely depends on the intensity of the training stimulus(11, 88).

Higher intensity and duration of the stimuli will cause greater levels of fatigue than that of lighter intensity or shorter duration(11, 87). The trade-off, according to this fitness-fatigue paradigm, is that benefit from these more intense and longer sessions will result in greater

adaptation (supercompensation) over time(10, 11, 87). Consequently, the term given to the declines in performance following these stimuli is “short-term overreaching” or “functional overreaching” (87, 89, 136). For short-term overreaching to turn into supercompensation, a period of recovery is needed before the next session(87, 89, 200). If continued high-intensity or prolonged training occurs while an athlete is in a fatigued state, an inability for the athlete to properly adapt may result. This maladaptation can result in both acute injury(73, 147) and overtraining syndrome(89, 136). While the mechanisms may differ between acute and overuse non-contact injuries, both may result from this fatigued state and in the absence of an athlete’s potential diagnosis of overtraining syndrome(65, 125, 145, 156, 188).

Understanding how injuries result from this fitness-fatigue dichotomy requires a framework. Kalkhoven et al.(129) provides a novel framework through which to observe the interplay between workload, inflammation, and non-contact or overuse injuries. This framework adds causal pathway to the work done by Bahr and Krosshaug(9) and Meeuwisse et al.(162) and provides a pathway for an athlete’s physiology, mechanics, and the tissue characteristics to affect the balance between injury and adaptation. Their framework has several subcomponents, beginning with the athlete’s physiology, then extending to tissue-specific strength and force properties, and finally including tissue-specific stress and strain. According to the model, an athlete’s physiology is comprised of modifiable, nonmodifiable, and external factors. This framework views biological tissue through the lens of material science and implies that the failure of muscle tissue results when excessive stress or strain exceeds the tissue’s ability to absorb such forces(78, 98, 179). These failures can be the result of a large singular event or repetitive, lower threshold events(78, 98, 179).

The framework by Kalkhoven et al., also includes method for tissue not to be injured(129). These tissues can undergo positive physiological and mechanical adaptations such as muscle hypertrophy(19, 52, 191-194), increased muscle strength(19, 52, 191-194), tendon adaptations(23), and bone mineral density improvements(41, 96, 128, 170) when the stress experienced does not result in structural failure. However, without proper rest and recovery these tissues can be damaged to the point of an injury occurring(37, 94, 233). The framework is recursive in that these injuries or adaptations will impact the athlete's physiology. As a result, this model is ideally suited for stress-, strain-, and overuse-related injuries.

Although there are several inflammatory biomarkers associated with overtraining that could be included in this framework, increases of c-reactive protein (CRP) have been observed in moderate and vigorous exercise(67, 84). CRP is a hepatic acute phase protein, whose synthesis is induced by the plasma cytokine interleukin-6 (IL-6) (178). CRP is a common biomarker of systemic inflammation, as well as tissue damage and necrosis(2). Normal CRP concentration levels in healthy adults has been reported to range between 0.8 mg/L and 3.0 mg/L (197). CRP concentration levels greater than 3 mg/L have been correlated with increased inflammation, cardiovascular disease, frailty, morbidity, and mortality(2, 187). CRP concentration levels can also increase 1,000-fold over 1-3 days after tissue damage or the onset of inflammation (93, 159). Increased circulating CRP levels can be present from 1 to 4 days and can be easily observed through blood or saliva sampling(40). Intense exercise, especially when it is paired with condensed recovery intervals, can yield chronic inflammation, through elevated IL-6, both locally (muscle tissue) and globally (whole body) (40, 181). This chronic elevation of IL-6 promotes a negative feedback loop on the suppressors of cytokine signaling (SOCS) family, thereby decreasing the signaling associated with human growth hormone (hGH) and insulin-like

growth factor-1 (IGF-1), which in turn inhibits the repair and adaptation mechanisms within the damaged tissue (40, 85, 103). A disproportion of fatigue to fitness has been shown in the literature to predispose athletes to greater risk of non-contact and overuse injuries(45, 78, 87). While IL-6 is the central promoter of CRP synthesis, its half-life (1 hour) is far shorter than that of CRP (19-hours). In addition, IL-6 may be systemically undetectable, yet be present locally, and still maintain elevated CPR levels(103). As a result, CRP may be a uniquely useful indicator for assessing chronic overtraining.

It is likely that the intense training that takes place during the pre-season practice period may cause a rise in CRP as a result of the increased physical stress placed on the athletes. This intense physical training, paired with the prolonged physical stress of in-season sport participation, may promote an environment of repetitive, chronic skeletal muscle damage. This repetitive skeletal muscle damage could in turn promote a negative feedback loop on SOCS, thereby promoting elevated levels of CRP. The inflammatory status of the muscle would, in theory, increase the risk of non-contact injury. If CRP levels are temporally associated with increased risk of sustaining non-contact injuries, then monitoring CRP may be a useful tool to evaluate conditioning and practice plans or to restructure the rules governing these time periods entirely.

Should CRP levels rise in response, and proportion, to increased workload rates, and if they are correlated with increased non-contact injury risk, then it would be reasonable to assume its rise from the workload rates alone. Therefore, the purpose of this study was to assess the relationships among the rate of external workload increase, C-reactive protein levels, and non-contact injuries during the preseason practice and in-season periods in college football. We hypothesized that the athletes with the highest increases in workload rate would have the highest

levels of CRP and would be at the greatest risk of sustaining non-contact injuries during the study period.

METHODS

Participants

Nineteen athletes from the same Division 1 American college football team were recruited for this study (mean ± SD: age: 21.1 ± 1.1 years, mass: 106.6 kg, and height: 188.2 ± 6.4 cm). All athletes were cleared by the university's sports medicine staff for sport participation. To best capture the variability within a football roster, at least two athletes were recruited from each of the following position groups: offensive line, tight-ends, wide receivers, running-backs, defensive ends, defensive tackles, linebackers, defensive backs. This study excluded quarterbacks and specialists. These positions were excluded due to the unique practice and game environments that these players encounter compared to their other teammates. Due to the limited number of devices, the football coaching staff assigned devices to players whom they deemed most likely to participate in competitions. Only athletes who were currently assigned global positioning devices were approached for recruitment. These athletes were categorized by their position and then assigned an identification number within that position group. A random number generator then selected two athletes from each group. These athletes were approached for inclusion in the study. Athletes were then assessed for any chronic diseases. If any of the athletes declined, the plan was to continue the random selection process until the allotted number of participants per position group was achieved; however, no athletes declined. All participants provided written informed consent, which permitted their deidentified data to be used for this

study. The Michigan State University Human Research Protection Program approved all experimental procedures for this study.

Quantifying Workload

Workloads were collected utilizing wearable global positioning system (GPS) devices sampling at 10 Hz (Optimeye S5, Catapult Innovations, Melbourne, AUS) during the 4-week preseason and 13-week in-season periods. These devices combine GPS with a tri-axial accelerometer sampling at 100 Hz, a gyroscope, and a magnetometer to derive an external workload metric known as Player Load (Catapult Innovations). The reliability, construct validity, and convergent validity of the components and algorithms to that are contained in these devices to ground-based and standardized treadmill running has been established by previous research(13, 57, 58, 100, 127, 132, 161, 183, 209, 214).

These devices were worn between the scapulae of the players in compression vests for all conditioning sessions and non-padded football practices. These vests came in varying sizes from small to xxxx-large which allowed for a compressed, comfortable fit for all players. During padded practices, players wore the devices in specially designed boxes mounted on their shoulder pads in a similar location to the vests. Players wore the same device for all activity sessions. Data were downloaded from the devices into the provided software (Openfield, Catapult Innovations, Melbourne, AUS). This software calculates workload as the sum of all accelerometer movements in the three-dimensional plane. This is a unit-less quantification as is defined by the manufacturer as:

$$\text{Player/Body Load} = \sqrt{\frac{(\alpha_{y1} - \alpha_{y-1}) + (\alpha_x - \alpha_{x-1}) + (\alpha_z - \alpha_{z-1})}{100}}$$

Where, y refers to the forward/backward acceleration, x refers to lateral acceleration, and z refers to vertical acceleration. Both ACWR and EWMA workload ratios were calculated. The ACWR, which utilizes the past 7 days as the acute workload and 28 days as the chronic workload periods, was calculated daily. The EMWA was calculated daily for both acute (past 7 days) and chronic (previous 21 days) workloads. The equation used to calculate the acute period was:

$$\text{Acute: } EWMA_t = \left[Load_t * \left(\frac{2}{7+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{7+1}\right)\right] * EWMA_{t-1}\right\}$$

The equation used to calculate the chronic period was:

$$\text{Chronic: } EWMA_t = \left[Load_t * \left(\frac{2}{21+1}\right)\right] + \left\{\left[1 - \left(\frac{2}{21+1}\right)\right] * EWMA_{t-1}\right\}$$

For this study, 'Load' refers to the accelerometer-derived Player Load metric, subscript t refers to the current observation, and subscript *t*-1 refers to the previous observation. The acute period was divided by the chronic to give a ratio value for each day. In the event of missing data (6 out of 1,704 observations, 0.35%), the position group average was supplemented into the data.

C-Reactive Protein Sample Collection

This study took place during the 2020 calendar year, which included the Covid-19 pandemic. Covid-19 precautions were in place to ensure as safe a sport participation environment as possible, which included atypical conditions and a deviation from an ideal collection protocol. Athletes were informed not to eat or drink 30 minutes prior to saliva collection. The first saliva sample collection took place on the Monday at the start of the first full week of pre-season

practice. To obtain the most consistent weekly CRP values, saliva samples were collected every Monday. Saliva samples were collected every Monday morning prior to the first activity session of the day. For each athlete, samples were collected at the same time of day in-conjunction with athlete screening. This collection time provided 36 to 44 hours of recovery from the last activity exposures. The saliva samples were collected using 2mL cryovials (SalivaBio LLC, Carlsbad, CA) and stored at -80℃ until assayed.

CRP measurement was performed using Human C Reactive Protein ELISA assay kits (ab108826, Abcam, Cambridge, MA) in conjunction with a microplate absorbance reader(iMark 19578, Bio-Rad, Hercules, CA). All assays were performed per the manufacturer protocols. Briefly, samples were thawed from -80°C storage at room temperature (21-23℃) and then centrifuged at 800 x g for 10 minutes. All reagents were brought to room temperature before use. Eight standards were developed from 16 ng/mL to 0 ng/mL through serial dilution for each plate, which detected a linear range of CRP from 0.25 ng/mL to 16 ng/mL. Each well received 50 µL of CRP standard or sample. Plates were then covered with sealing tape and incubated for 2 hours at room temperature on an orbital table. Plates were washed manually and were inverted and decanted to remove all liquid. Each well then received 50 µL of 1X Biotinylated C-Reactive Protein Antibody. Wells were covered with sealing tape and incubated for 30 minutes at room temperature. The previous wash procedure was repeated, and 50 µL of 1X SP Conjugate was added to each well and incubated, uncovered, for 30 minutes in the same manner as prior incubations. The wash procedure was repeated and followed by the addition of 50 µL of Chromogen Substrate to each well. After the plates incubated for 15 minutes at room temperature, 50 µL of Stop Solution was added to each well. Plates were then read immediately on the microplate absorbance reader, at a wavelength of 450 nm, with a pathlength correction of

100 µL. Data were acquired, and reports exported with the accompanying software (Microplate Manager Software 6, Bio-Rad, Hercules, CA).

Definition of Exposure

Practice and competition sessions were cataloged as activities. An athlete exposure was defined as one athlete participating in one activity. All participations and durations were confirmed by the team's practitioners for each athlete.

Definition of Injury

The team's sports medicine staff diagnosed all injuries during the data collection period. Injuries were categorized using the distinctions set forth in the NCAA Sports Injury Surveillance program(133). Lower-body and trunk injuries with non-contact or overuse mechanisms were included in the analysis. This decision was made because of the possibly that these injuries occur due to large increases in the rate of activity exposure(87, 94). Time-loss was defined as any injury where an athlete was unable to participate in subsequent conditioning sessions, practices, or competitions.

Statistical Analysis

All statistical calculations and analyses were completed using the Stata IC v16.1 software package (StataCorp LLC, College Station, TX). A one-way repeated measures ANOVA was run to determine if there were differences in CRP concentrations across time. For further assessment

of CRP, previous 7-day loads, workload ratios, and injury information variables were collated into weekly values. Ordinarily, the length of the days utilized in the chronic workload calculation (i.e., 28-day average) would delay the utilization of any workload ratio calculations until the chronic time period requirement had been met. To utilize as large a data set as possible, previous research assigned an arbitrary starting workload ratio value of 1.00 to the beginning of their data sets (168, 188). However, the athletes in this study had been undergoing conditioning for several weeks prior to the start of their football practice activities. As a result, this study utilized those weeks of training data to provide more accurate workload ratios for the beginning of the CRP collection period. Once weekly values were compiled, a series of panel regressions were performed. Hausman's test was used to determine if random effects or fixed effects should be included in each model. The first panel regression assessed the impact of previous 7-day load on the following Monday's CRP concentration. The second and third regressions assessed the impact of the ACWR and EWMA on CRP concentrations. Finally, logistic regressions were planned to assess the association between each workload ratio, CRP, and subsequent time-loss non-contact injury. Statistical power and effect sizes were also assessed.

RESULTS

There were 18 total injuries sustained by 12 players during the 12-week data collection period. The total injury rate for this period was 9.07 per 1000 hours of exposure (HE), or 15.04 per 1000 activities of exposure (AE). Of the 18 injuries, 3 were the result of a non-contact mechanism (HE: 1.51; AE: 2.51), and only 1 of these injuries resulted in time-loss (HE: 0.50; AE: 0.84). These injuries are presented in Table 5.1 by week. For a list of all observed injuries see Supplemental Table 5.1. Overall, no correlations were observed between the 7-day cumulative load and either all-cause injury occurrence (Pearson's r = 0.04) or non-contact injury occurrence (r = 0.01) (42).

Table 5. 1. Non-Contact Injury, ACWR, EWMA, and CRP descriptive data in the week preceding injury.

Injury Week	Injury Location	Injury Diagnosis	Injury Mechanism	Time-Loss Injury	CRP (mg/L)	Load (AU)	ACWR Ratio	EWMA Ratio
1	Hip / Thigh	Strain	Noncontact	No	0.462	1561	1.76	1.20
6	Hip / Thigh	Strain	Noncontact	Yes	0.098	2096	1.72	1.15
7	Hip / Thigh	Strain	Noncontact	No	0.044	2699	1.21	1.00

A total of 211 CRP samples were collected during the investigation. In total, there were 17 observations with missing CRP data (228 total observations, 7.45%). Nine of these missing observations were due to athletes being injured or quarantined, and thus permitted to avoid the training facility. The overall average CRP value for the dataset was 1.34 mg/L (95% CI: 1.08 to 1.59) and had a standard deviation of 0.13 mg/L. As such, samples with values beyond 3 standard deviations from the mean (greater than 5.22 mg/L) and lacking corresponding injury or illness history were considered outliers due to errors in collection and removed from the analysis

(7 unique athletes, 8 of 211 collected observations, 3.79%) (113). The outlier samples were collected from seven athletes. The two samples collected from a single athlete occurred 3 weeks apart. Average weekly CRP concentrations and 95% confidence intervals are displayed in Figure 5.1. Individual weekly load, CRP, and injury occurrence are presented in Supplemental Figure 5.1. Weekly CRP levels by individual are also presented in Supplemental Figure 5.2.

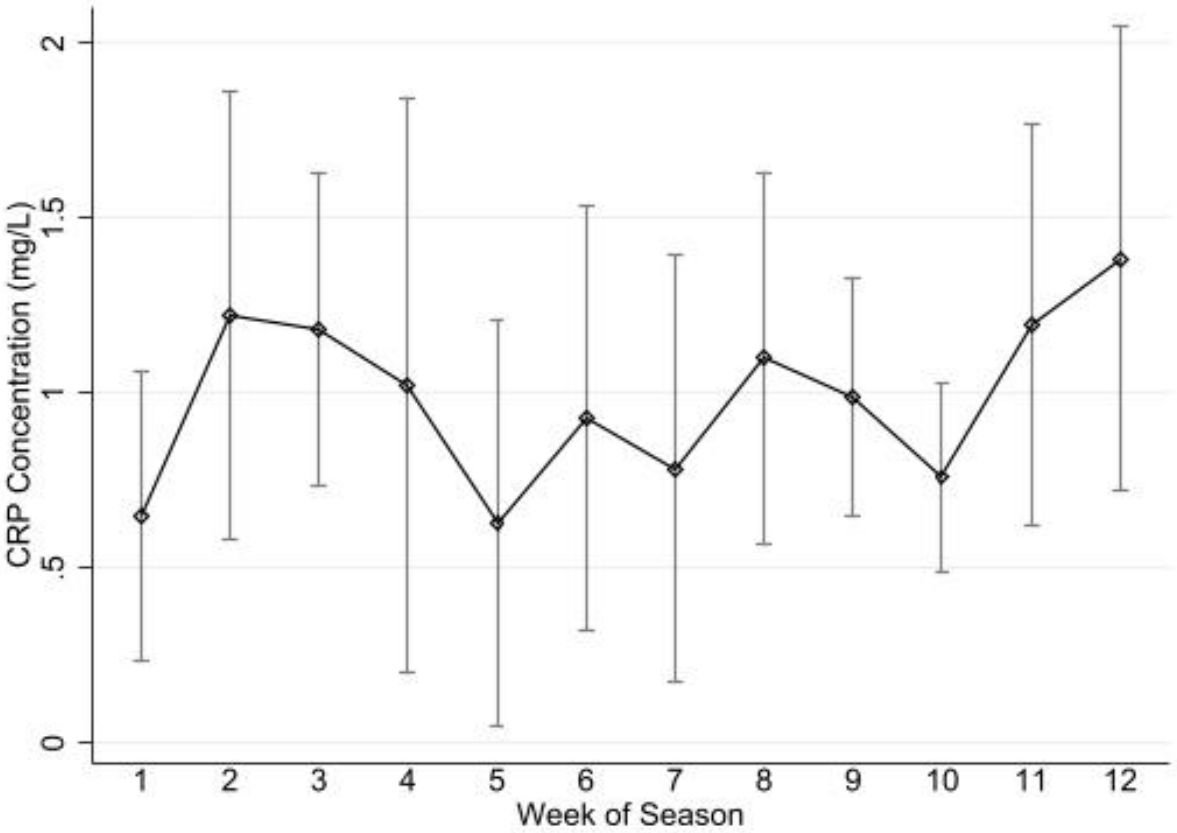

Figure 5. 1. Average CRP with 95% confidence intervals by week of season.

A one-way repeated measures ANOVA was run to determine if there were differences in CRP concentrations across time. The result from this test ($F_{11,176} = 1.41$; $p = 0.17$) indicates there was no significant difference in CRP concentration across time. The partial eta-squared (η^2) for 19 athletes across 12 repeated measures, with a correlation among repeated measures of .1346 was 0.08 ($\alpha = .05$, 1 group). This corresponded to a power of 0.91 and an effect size (f) of 0.29.

The average weekly load ($\pm$ std. dev.) for the investigation period was 1837 $\pm$ 791 AU. Load was determined to vary across time ($F_{11,192} = 3.97$; $p < 0.001$) with an effect size of 0.48 ($\eta^2 = 0.19$; Power = 0.999). The average load from the previous week had a fair correlation with average CRP concentration at the beginning of the following week (r = 0.38). However, when calculated individually, correlation ranged from -0.68 to 0.66. Additionally, the change in CRP concentration was poorly correlated (r = 0.15) to the change in load from week to week. Previous 7-day average load and current week CRP concentration values are included in Figure 5.2.

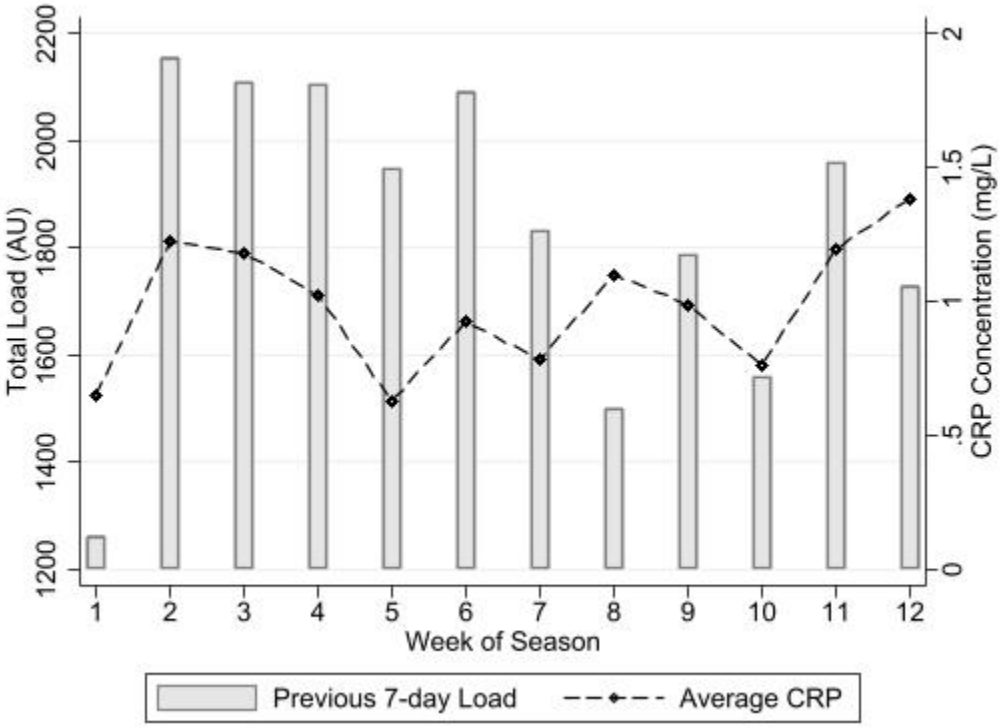

Figure 5. 2. Average load and CRP concentrations by week of season.

Note: Week of season corresponds to the week CRP samples were taken. Samples were taken on Monday's and therefore plotted with the previous 7-day load.

The average EWMA ratio value (± std. dev.) was 0.99 ± 0.33, and the average traditional ACWR value was 1.17 ± 0.61. EWMA and traditional ACWR values at time of sample collection were poorly correlated with CRP concentrations (r = -0.11; -0.07). Weekly averages for load, EWMA, and traditional ACWR values are included in Figure 5.3.

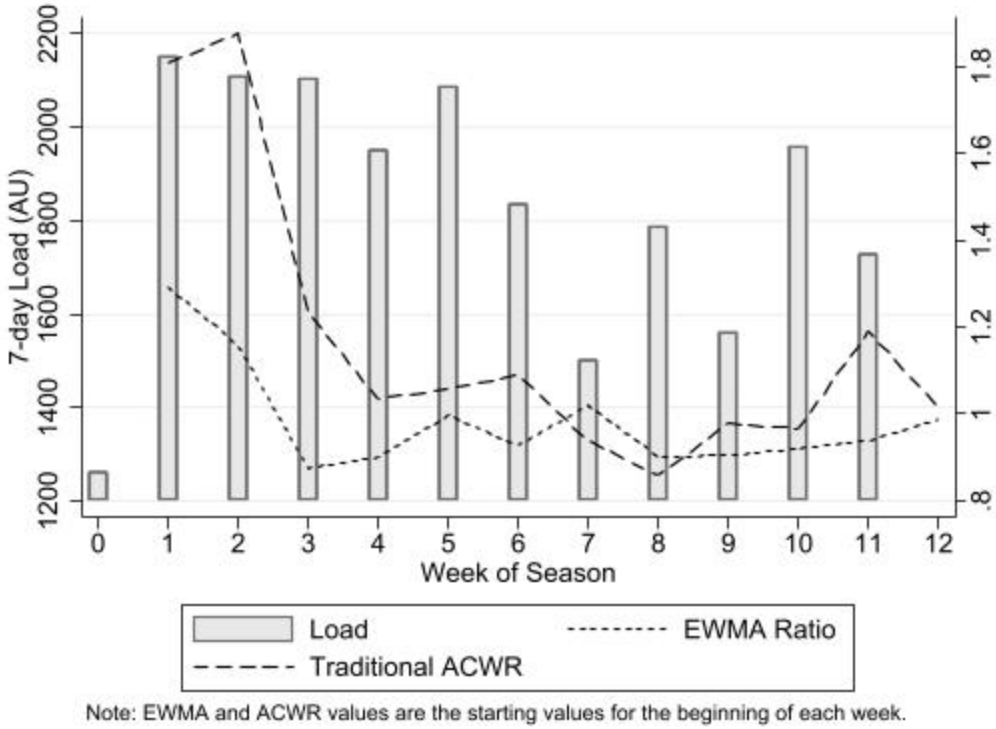

Figure 5. 3. Average load, traditional ACWR, and EWMA ratio values by week.

The first panel regression model assessed the impact of the previous week's load on the following week's CRP concentration. Hausman's test results (Wald $X^2 = 1.01$; $p = 0.32$) indicated that a panel regression model with random effects could be used. The results from this model suggested that increasing weekly load (Wald $X^2 = 0.48$; $p = 0.49$) was not associated with the following week's CRP concentration.

The second and third models assessed the traditional ACWR and EWMA values, respectively. Panel regression models with random effects were also used for these results, as the Hausman's test results for ACWR (Wald $X^2 = 0.01$; $p = 0.93$) and EWMA (Wald $X^2 = 2.14$; $p = 0.14$) were both nonsignificant. Both the ACWR (Wald $X^2 = 1.47$; $p = 0.23$) and the EWMA (Wald $X^2 = 1.54$; $p = 0.21$) were not associated with CRP concentrations.

We were unable to run the planned logistic regression to assess the association between workload ratios, CRP, and subsequent time-loss non-contact injury due to only having one event occur during the observational period. The athlete who sustained the injury had a starting CRP value of 0.098 mg/L for the week. This athlete had been returning to play following a lower body contact injury two weeks prior. The athlete had respective ACWR and EWMA ratio values of 1.72 and 1.16 prior to injury. The week following injury, this athlete had a doubling of their CRP concentration to 0.175 mg/L. Both pre- and post-injury CRP concentration values were within the normative range reported in athletes from other sports(71). Though it is clinically positive to have only one case of non-contact injury, no scientific conclusions can be drawn from this isolated event.

DISCUSSION

The purpose of this study was to assess the relationships among external workload, CRP, and non-contact time-loss injuries. Results from this study found that while weekly load was determined to have varied across time, CRP concentrations did not. Furthermore, weekly change in workload was poorly correlated with change in CRP. Ultimately, regression analysis failed to yield statistically significant relationships between workload, CRP, and non-contact time-loss injuries.

Our hypothesis that athletes would experience increases in their salivary CRP concentrations during the beginning of the pre-season practice period, due to increasing workloads, was not supported. Additionally, this study demonstrated no association between CRP and either the traditional ACWR or EWMA ratio values. There were several planned regression models sought to assess CRP concentrations, weekly load, and the workload ratios on non-contact injury outcomes. However, given the rarity of these injuries in the observed athletes (3 non-contact injuries with 1 time-loss injury), these models would yield biased results, and thus could not be utilized in the current study(51).

The non-contact time-loss injury rate (0.84 AEs) reported in this study is significantly lower (z-score = -14.75, $p < 0.001$) than the injury rate which has been reported in previous research (1.43 $\pm$ 0.04 AEs) (133). However, it should also be noted that the rate of all-cause time-loss injuries in this study was 12.53 AEs. This rate is significantly higher (z-score = 43.12, $p < 0.001$) than what has been reported in previous research (7.14 $\pm$ 0.12 AEs). These results may be due in part to the style of practices coordinated by this team, such that contact is more prevalent than what has been observed in previous research, but this is pure speculation.

There are potentially several reasons for the absence of association between CRP and increased workload reflected in this study. The first reason, as discussed earlier, may be due to the period selected for study. Simply put, the high contact nature of practices and competitions during the pre-season and in-season periods may have provided a limited opportunity for non-contact injuries to occur. Alternatively, measuring CRP levels during the limited contact periods of summer or winter conditioning periods may better discover the true nature or inflammation and non-contact injury risk. Secondly, due to the uncertainty of scheduling because of the COVID-19 pandemic, establishing true baseline CRP concentration values was unobtainable. Though CRP concentrations were recorded at week 1, when preseason practices began, athletes had already been exposed to 5 weeks of conditioning. Previous research has shown that this regular training exposure can provide anti-inflammatory response , including the inhibition of Tumor Necrosis Factor α (TNF-α) through the production of anti-inflammatory proteins IL-1ra and IL-10. The increased IL-1ra and IL-10 are the result of circulating IL-6 post exercise(40, 181). By inhibiting TNF-α, these proteins inhibit cell necrosis and apoptosis, thus promoting positive adaptations such as muscle hypertrophy. Due to the COVID-19 pandemic, and the uncertainty surrounding the football schedule, notice of when the start of preseason training would begin was given last-minute, and therefore earlier samples were not obtained. Finally, there may not be an association between chronic systemic inflammation and non-contact injury risk. Average CRP concentrations hovered around the 1 mg/L value that is associated with healthy individuals for the entirety of the observational period. The 95% confidence interval ranged widely from near 0 mg/L to 2 mg/L but remained below the 3 mg/L associated with inflammation and cardiovascular risk (187). Inflammation may still contribute to injury risk, but

the effect may be local to an individual muscle group and thus not able to be adequately assessed via systemic methods.

While this study failed to provide a link between increased workload, measured using ACWR or EWMA methods, and non-contact injury by way of an inflammatory mediator, it also failed to yield statistically significant association between increased workload and non-contact injury, period. Numerous papers have pointed to a potential relationship between increased workload and subsequent increased non-contact injury risk(48, 65, 108, 167-169, 186, 189). This study contained 260 activity observations where athletes had ACWR values of at least 1.50 and 116 days with EWMA values greater than 1.50. Number of observations with ACWR or EWMA values greater than 2.00 were 106 and 65, respectively. Research by Hulin et. al (116) found that ACWR values greater than 2.11 were associated with the highest risk of injury in the current week (16.7% injury risk). Of the 15 time-loss injuries (contact and non-contact combined) sustained during this study, 5 were within 7 days of an athlete experiencing an ACWR value greater than 2.11. Dividing these injuries by the total number of activity observations (1,070), as done by Hulin et. al, yields an injury risk of only 0.46%. Additionally, 9 injuries occurred when ACWR values between 0.8 and 1.3 were experienced. Using these numbers, one would conclude that injury risk was higher (0.84%) when athletes were within the supposed 'ideal' range than when they experienced higher ACWR values.

According to prior research in collegiate football, when low chronic EWMA load values (< 85 AU) were combined with either low (< 0.8) or high (> 1.30) ratio values there was an injury probability of at least 97.8%(188). The present study had 52 observations which fit these criteria, and which could be used to support these injury probability claims. However, there was not a single occurrence of non-contact injury, time-loss or otherwise, when either low or high

chronic loads were combined with low or high workload ratio values. Rather, all 3 non-contact injuries occurred within the 0.8 – 1.3 range. These results should serve to temper the association previously made between workload ratios and injury risk in college football.

Potential Strength & Limitations

This study had limitations. The main limitation is the absence of non-contact time-loss injuries. Though clinically positive, a larger number of injuries is required to properly utilize the statistical analyses necessary to assess the association of inflammation and injury. Therefore, this study would have benefited from a larger number of subjects over a longer period. Additionally, the unique schedule of the 2020 football calendar, because of the COVID-19 pandemic, stresses the ability to relate these results to either previous research or the normal football environment. There were variations in cumulative week load that were likely the result of cancelled games. These game cancellations may have promoted positive adaptations through rest and limited contact which otherwise would not typically occur in a traditional football year. Furthermore, our study did not consider smoking or drug habits, which may increase CRP concentration levels (55). This study, however, does possess several strengths. First, this study was able to prospectively assess the relationships among workload, inflammation, and injury in collegiate football players using an injury framework. This study also assessed the relationship between two common workload ratios and injury utilizing continuous methodologies proposed by recent literature(36). Finally, our study was able to compare, and find significant difference between, the observed injury rates with rates reported several years ago.

Conclusions

In this study, we were unable to demonstrate that acute increases in workload, as displayed by either absolute 7-day cumulative load or acute:chronic workload ratios, leads to increased systemic inflammation, measured via salivary C-Reactive Protein concentrations, which results in increased risk of non-contact injury. Additionally, this study tempers the assertions made by prior research that specific workload ratio values predispose athletes to a greater risk of injury. These findings should serve to 1) caution practitioners from using these calculations in isolation, and 2) bolster their efforts to compile larger datasets and investigate the inflammation – injury relationship further.

APPENDIX

Table 5. 2. Injury, ACWR, and CRP descriptive data in the week preceding injury.

Injury Week	Injury Location	Injury Diagnosis	Injury Mechanism	Time-Loss Injury	CRP (mg/L)	Load (AU)	ACWR Ratio	EWMA Ratio
1	Knee	Sprain	Contact	Yes	0.139	239	2.03	2.49
1	Trunk	Strain	Contact	Yes	0.168	1681	2.23	0.82
1	**Hip / Thigh**	**Strain**	**Noncontact**	**No**	**0.462**	**1561**	**1.76**	**1.20**
2	Hand / Wrist	Fracture	Contact	Yes	0.052	2601	1.85	1.31
2	Hip / Thigh	Strain	Contact	Yes	2.856	2982	1.85	1.13
2	Shoulder / Clavicle	Sprain	Contact	Yes	3.441	1735	2.55	1.39
3	Neck	Contusion	Contact	Yes	2.551	2936	1.81	1.10
3	Ankle	Sprain	Contact	Yes	1.223	2225	1.41	0.80
3	Hip / Thigh	Strain	Contact	Yes	6.014	2303	1.21	0.96
4	Head / Face	Concussion	Contact	Yes	0.346	2598	1.00	0.69
4	Shoulder / Clavicle	Sprain	Contact	Yes	-	2694	1.28	1.02
4	Ankle	Sprain	Contact	Yes	2.756	2574	1.14	1.07
6	**Hip / Thigh**	**Strain**	**Noncontact**	**Yes**	**0.098**	**2096**	**1.72**	**1.16**
7	**Hip / Thigh**	**Strain**	**Noncontact**	**No**	**0.044**	**2699**	**1.21**	**1.00**
7	Ankle	Sprain	Contact	Yes	4.446	2457	1.08	0.98
11	Knee	Sprain	Contact	Yes	0.810	2081	1.17	0.73
12	Head / Face	Concussion	Contact	Yes	0.933	2560	0.92	0.94
12	Hip / Thigh	Strain	Contact	No	0.825	1280	1.02	0.89

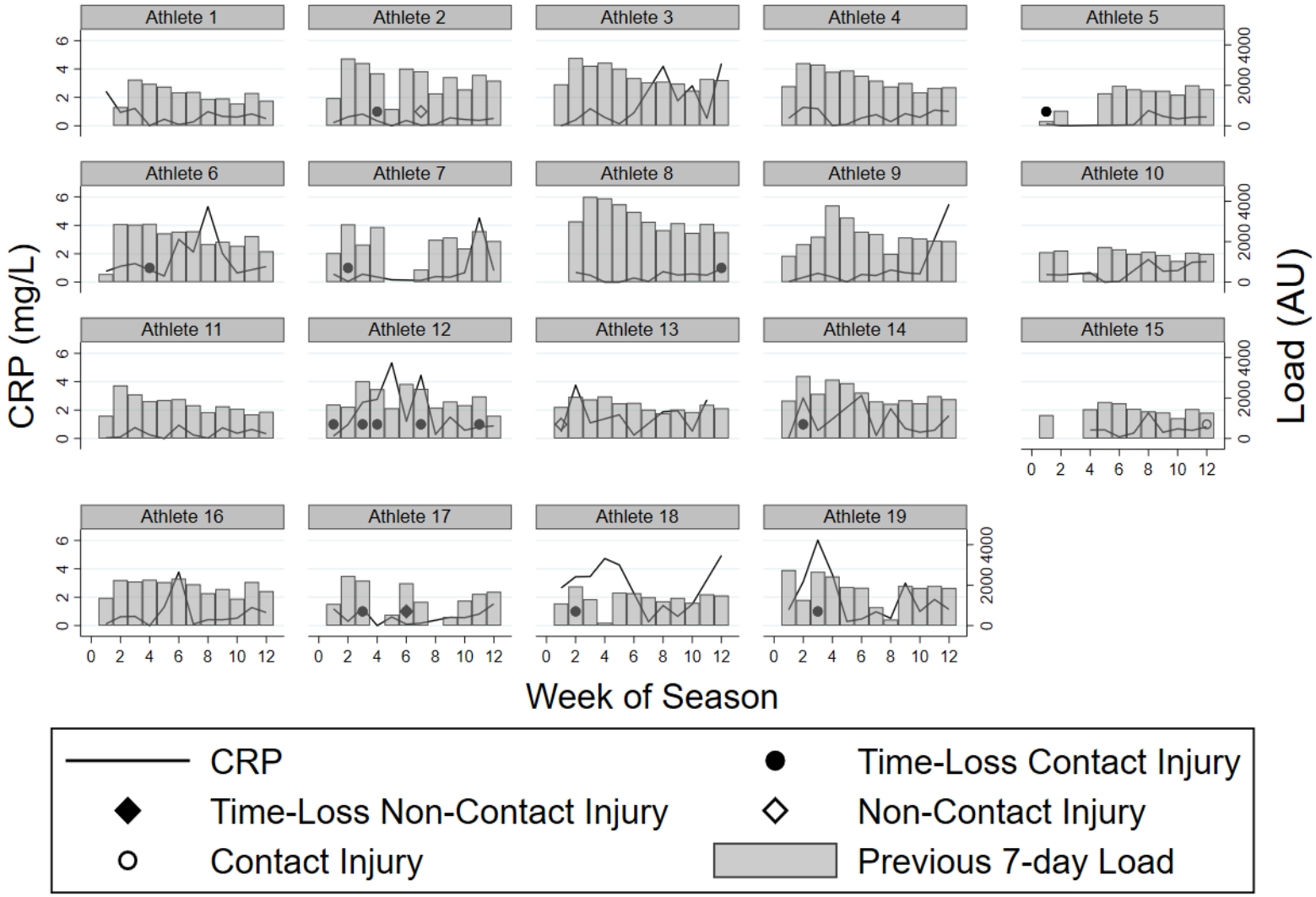

Figure 5. 4. Average CRP with 95% confidence intervals by week of season.

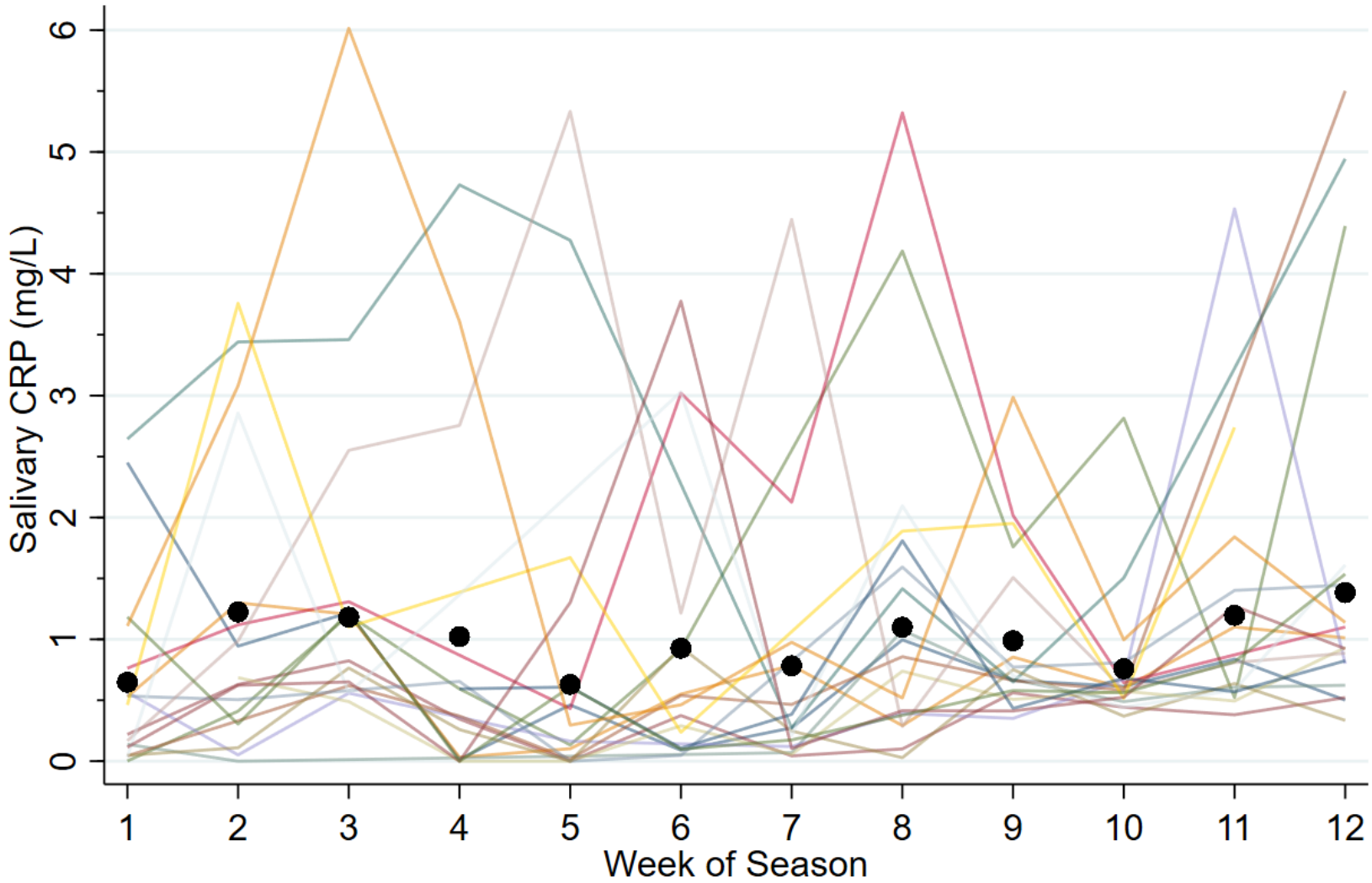

Figure 5. 5. Average and individual CRP levels by week of season.

Consent Forms

Research Participant Information and Consent Form

Study Title: A comparison of C-reactive protein levels, external workloads, and injury rates in division 1 American football players: C-Reactive Protein Sub-Study

BRIEF SUMMARY
You are being asked to participate in a research study involving 30 division 1 American football players. Researchers are required to provide a consent form to inform you about the research study, to convey that participation is voluntary, to explain risks and benefits of participation including why you might or might not want to participate, and to empower you to make an informed decision. You should feel free to discuss and ask the researchers any questions you may have.

You are being asked to participate in a research study of investigating the interaction between external workload, an internal biomarker for inflammation, and injury / illness occurrence during the pre-season and in-season periods of Division 1 football. Your participation in this study involves a small finger prick once a week from June thru November, 2020. Your participation also involves expectorating into a small tube at each time of blood collection. You will also be asked to allow your wearable data to be used in this study. In addition, you will be asked to allow the athletic medicine team to report basic information about any injuries or illnesses you sustain during the course of the data collection period. Your participation is voluntary, and you may withdraw consent at any time during the data collection period.

The most likely risks of participating in this study are the standard risks associated with participation in collegiate football.

You will not directly benefit from your participation in this study. However, your participation in this study may contribute to the understanding how athletic participation increases are associated with increased injury and illness risk.

PURPOSE OF RESEARCH

The purpose of this research study is to investigate whether increased activity rates elicit an internal inflammatory response which subsequently increases the risk of non-contact injury or illness. Understanding this relationship can allow for more appropriate practice planning, mediating interventions, and/or the potential for rule changes at the NCAA level to minimize injury risk.

WHAT YOU WILL BE ASKED TO DO

Allow the study team access to your Catapult monitoring data from June thru November of this year (2020). You will also consent to having a small amount of blood drawn from your index finger every Monday during the duration of the study. You will also be asked to expectorate into a small tube at each time of blood collection. Finally, you must allow the athletic medicine staff to report basic information on any injuries or illnesses you sustain during the study period. This information will include injury/illness type, body location involved (if injury), whether it was received from contact during an activity, and any activity time missed or modified during the study duration. All personal information identifying you will be removed from the study.

Approved by a Michigan State University Institutional Review Board effective 6/15/2020.
This version supersedes all previous versions. MSU Study ID STUDY00002883.

POTENTIAL BENEFITS

You will not benefit personally from being in this study. However, we hope that in the future other people might benefit from this study because the data provided will help administrators and coaches design more optimal policies and training plans to minimize the risk of injury with football participation.

POTENTIAL RISKS

The major risk for participating in this study is a data breach. Other minor risks, including fainting, illness, and infection, are associated with the drawing of blood. All injury data will be void of identifying information and your participation will be anonymous.

PRIVACY AND CONFIDENTIALITY

Participants will be assigned a unique study ID number, which will be used within all data files. The informed consent forms and identifying information will be stored separately from all collected data. All wearable and injury data will be stored on either password protected files within locked offices at the Skandalaris Football Building, or online within the Catapult Sports web application. This application is HIPAA compliant and is part of the normal use of these devices prior to this study. The blood marker data will be stored in a password-protected file in the locked office of the study coordinator at the Skandalaris Football Building. The data will be kept for at least three years after the project closes and that the data will be accessible to the researchers on the study and the human research protection program. In addition, that the data will be kept confidential to the maximum extent allowable by law. Identified injury data will be stored within athletic medicine's electronic medical records software as is current standard practice. All data will remain at Michigan State University and will not continue on with the study coordinator should they leave the university. Study findings will be reported in the aggregate form so that individual participants cannot be identified.

YOUR RIGHTS TO PARTICIPATE, SAY NO, OR WITHDRAW

You have the right to say no to participation in the research study. There will be no consequences if you decline and you will not be criticized. You will not lose any benefits that you normally receive.

COSTS AND COMPENSATION FOR BEING IN THE STUDY

There are no costs or compensation to you for being in the study.

RESEARCH RESULTS

Approved by a Michigan State University Institutional Review Board effective 6/15/2020.
This version supersedes all previous versions. MSU Study ID STUDY00002883.

A copy of the study will be provided to you should you request it.

FUTURE RESEARCH

Information that identifies you will be removed from the study results. This information includes name, age, and injury information that may make it possible to identify your involvement. Your de-identified information will not be reported on individually in the study. After personal identifiers are removed from the data and biospecimens, the information or biospecimens could be used for future research studies or distributed to another investigator for future research studies without additional informed consent from the subject or the legally authorized representative.

CONTACT INFORMATION

If you have concerns or questions about this study, such as scientific issues, how to do any part of it, or to report an injury, please contact the researcher Bill Burghardt at 771 Chestnut Rd, East Lansing, MI 48824 or email burghardt@ath.msu.edu or 517-927-7366. You may also contact the Principal Investigator, Dr. Karin Pfeiffer at 308 W. Circle Dr., Room 27R IM Sports Circle, East Lansing, MI 48824, kap@msu.edu, 517-353-5222.

If you have questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or e-mail irb@msu.edu or regular mail at 4000 Collins Rd, Suite 136, Lansing, MI 48910.

DOCUMENTATION OF INFORMED CONSENT.

Your signature below means that you voluntarily agree to participate in this research study.

_____ _____

Signature Date

You will be given a copy of this form to keep.

Approved by a Michigan State University Institutional Review Board effective 6/15/2020.
This version supersedes all previous versions. MSU Study ID STUDY00002883.

MSU HEALTH CARE, INC. AUTHORIZATION TO USE OR DISCLOSE HEALTH INFORMATION FOR RESEARCH

Name: _____

Date of Birth: _____

If you sign this document, you give permission to all health care providers at the MSU Health Care to use or disclose (release) your health information that identifies you for the research study described below.

TITLE: A comparison of C-reactive protein levels, external workloads, and injury rates in division 1 American football players: C-Reactive Protein Sub-Study

PURPOSE OF RESEARCH: The purpose of this research study is to investigate whether increased activity rates elicit an internal inflammatory response which subsequently increases the risk of non-contact injury or illness. Understanding this relationship can allow for more appropriate practice planning, mediating interventions, and/or the potential for rule changes at the NCAA level to minimize injury risk.

DESCRIPTION OF INFORMATION TO BE USED OR DISCLOSED (RELEASED) FOR THIS RESEARCH INCLUDES: This study asks to collect basic injury description information from your medical records for the dates within the study collection period. This injury information will include mechanism of injury (i.e. contact, non-contact, chronic), diagnosis (i.e. contusion, concussion, dislocation, muscle/tendon strain), body part injured (i.e. knee, head, neck, arm/elbow, lower leg), and time-lost from sport participation. This study will also collect the Catapult Sport GPS movement data from the wearables you wearing during team activities. Your information will be anonymized and there will be no data published in the study on you as an individual. All data will be reported on by position and/or the compiled team data.

In addition to the injury and movement data collected, you may be asked if you would be willing to participate in a sub-study involving a finger prick to measure c-reactive protein in a small amount of blood. This prick is similar to blood sugar testing and will only take place once per week. You will also be asked to provide a saliva sample obtained by expectorating into a tube. You may decline at any time to participate in this study. This data will also be anonymized and reported on in group contexts and not individually.

THE HEALTH INFORMATION LISTED ABOVE MAY BE USED AND/OR DISCLOSED (RELEASED) TO: William Burghardt (Study Coordinator), Dr. Karin Pfeiffer (Primary Investigator), the Michigan State University Human Research Protection Program

V20-01 (5-26-2020)

MSU HEALTH CARE, INC. AUTHORIZATION TO USE OR DISCLOSE HEALTH INFORMATION FOR RESEARCH

You may refuse to sign this authorization and your refusal will not affect your ability to obtain treatment, however, it may affect your ability to participate in this research study.

You may change your mind and revoke (take back) this Authorization at any time, except to the extent that MSU Health Care has already acted based on this Authorization. To revoke this Authorization, you must write to: The MSU Health Care privacy officer at Michigan State University, 909 Wilson Road, Room 415, East Lansing, MI 48824.

MSU Health Care is required by law to protect your health information. By signing this document, you authorize MSU Health Care to use and/or disclose (release) your health information for this research. Those persons who receive your health information may not be required by Federal privacy laws (such as the Privacy Rule) to protect it and may share your information with others without your permission, if permitted by laws governing them.

EXPIRATION: Your Authorization to disclose the above information expires at the end of the research study.

_____

Signature of individual participant or personal representative Date

_____

Printed name of individual participant or personal representative

_____

If applicable, a description of personal representative's authority to act for the individual participant

YOU WILL BE PROVIDED A COPY OF THE SIGNED FORM

A COPY OF THE SIGNED FORM MUST BE PROVIDED TO MSU HEALTH CARE

V20-01 (5-26-2020)

CHAPTER 6

DISSERTATION SUMMARY AND RECOMMENDATIONS

Summary of results

Minimizing the occurrence of injuries is critical for athlete health, development, and overall team success(69, 87, 123). In collegiate football, a greater percentage of injuries occur during practice than competitions (59.5% vs 40.5%)(133). Non-contact and overuse injuries account for approximately 35% of these injuries(133). A potential contributor to these injuries may be the rate at which they increase their sport training and participation(68, 81, 102, 114-116, 150, 151, 156, 169, 186, 188, 189, 204, 219). Novel wearable devices have been used to quantify this activity across a variety of sports(59, 68, 83, 115, 116, 125, 149, 150, 167-169, 204). Several sport-specific calculation methods have been developed to quantify an athlete's recent activity to their past activity history(102, 155). However, several authors have questioned the injury-framework and mathematical underpinnings of these calculations(36, 119, 120, 122, 163, 216). Additionally, collegiate football training and participation is a year-round process. Current research has addressed the pre-season and in-season periods but has failed to address the injury rates for winter conditioning, spring practice, or summer training. Therefore, the overall purposes of this dissertation were to 1) utilize modern statistical practices to assess the relationship between injuries, workload, and workload ratios between two different teams, 2) determine the non-contact injury rates for each phase of the calendar year and assess the relationship to workload and workload ratios, and 3) to evaluate if systemic inflammation may be a mediator between workload and non-contact injury events.

Chapter 3: Multi-team analysis

The first major objective of our investigation focused on the association between acute:chronic workload ratio calculations and non-contact injury risk across multiple teams. We hypothesized that both teams would have similar workloads, workload ratios, and non-contact injury occurrences, however the values for each team would be significantly difference across phases of sport training and competition. Both teams reported 44 non-contact injuries apiece, however, reported time-loss injuries were different (Team 1: 6; Team 2: 17). This both confirms and refutes the hypothesis of similar injury occurrences. Our results also confirmed our hypothesis that workloads and workload ratios were significantly different between phases of the year; however, these variables were also significantly different between teams for the pre-season and in-season phases. This finding does not support our hypothesis of team similarity.

We also hypothesized that the EWMA workload ratio calculation would have greater association to non-contact injury than the ACWR calculation, and that the team-specific models would yield greater association than the combined models. Though both calculation methods were significantly associated with injury, our results, obtained by measuring the area under the curve for both ROC and P-R curves, failed to demonstrate any model superiority over the others. In addition, the results of low precision and low recall, lends support to the critics of the workload ratio metrics(36, 142, 173, 174, 216).

One significant issue in assessing the relationships between workload and injury is choosing which specific variables to include for workload. Previous research has a myriad of different variables as the workload metric including distance, distance at certain velocities, sRPE, jumps, pitch counts, heart rate-based measures, and accelerometer-derived “load”. Each measure has its value depending on the sport and environment; however, significant drawbacks

are also associated with each. Distance provides a useful "volume" measure but does not account for intensity of movement. Distance at certain velocities accounts for intensity but may not capture the entire volume of activity. Jumps and pitch counts are sport-specific and require the use of accelerometers with adequate algorithms, or manual reporting by an observer. Heart-rate-based measures and sRPE provided data into the perceived intensity of an activity but do not provide context. Additionally, sRPE measures require an observer to collect responses from each athlete at specific time intervals, making it more labor intensive. We chose accelerometer-derived "load" because it provides a measure that accounts for the volume of activity as well as intense movements. Additionally, these devices require less manual labor in data collection than sRPE and other sport-specific measures. Finally, the use of accelerometer-derived load permitted use data collected indoors where distances and speeds were not measurable due to the ceiling blocking the use of GPS satellites, which improved the scope of our research. Given both teams were already using the same devices, it also provided us with an objective data collection tool.

The wearable devices used by these teams provides numerous variables that could be of particular interest, such as acceleration counts at different intensities, change of direction measures, and contacts. However, the objective of our study was to determine the relationship between previously reported measures. Given our models determined low clinical utility of workload and workload ratios, it may be that the inclusion of these other variables in future research may improve these models.

In conclusion, neither workload ratio calculation method nor dataset resulted in a model that was better fitting than another for the assessment of the association between workload, workload ratios, and non-contact injuries. While these variables were associated with injury, the

models indicated relatively low probability of injury. Additionally, the negative association demonstrated by workload, and inverted-U association by workload ratios, refute the findings of previous research in college football(188, 189).

Chapter 4: Multi-year analysis

The second major objective of this dissertation was to evaluate the association between workloads, workload ratios, and non-contact injury occurrence across the full calendar year of sport participation. We were able to use nearly 3 years of data from the same Division 1 football team to compare these associations across the winter conditioning, spring practice, summer conditioning, pre-season practice, and in-season phases of sport participation. We hypothesized that both workload ratio calculations would be significantly associated with increased non-contact injury risk during each phase of the year, but that EWMA would possess greater association and model fit than ACWR.

Our results did confirm the significant association with workload ratios and injury for each phase of the year, however, our hypothesis on the direction of the association was refuted. For each phase, increased workload was associated with decreased injury probability, and increased workload ratio demonstrated an inverted-U relationship. Our results also did not support the EWMA calculation to be a superior method to ACWR. Both EWMA and ACWR calculation methods yielded area under the curves for ROC of 0.83 and had non-significantly different areas for Precision-Recall (0.0110 vs 0.0185). The Precision-Recall results demonstrated similar low precision and low recall to our results from Chapter 3. Our findings contrast previous work demonstrating that workload and workload ratios were positively associated with non-contact injury, and give pause to the manipulation of these metrics as a

method to reduce injury occurrence(3, 16, 38, 39, 57, 68, 95, 110, 143, 184, 188-190, 195, 196, 198, 203, 207, 217, 218, 223).

A major hurdle of our research was the sparseness of non-contact time-loss injuries. The relatively low number of injuries compared to observations means that normally useful statistical tools such has frailty models and panel regressions would instead provide biased results for determining association to injury(134). We attempted to overcome this hurdle by observing a multi-year dataset. However, this observation resulted in an unbalanced panel which, in turn, yields its own distinct issues and estimation restrictions. In order to capture a sufficient number of injuries(226), future research should seek to build a database comprised of multiple teams.

In addition to these hypotheses, the results from our study also highlight the need to monitor the full calendar year of sport participation. The winter conditioning, spring practice, and summer conditioning phases accounted for 39% of all non-contact injuries observed. The IRRs of these phases were also greater than the in-season period. As future research looks to reduce injury occurrences, these phases should not be left out of observation.

In conclusion, our study supports workload and workload ratio collection. However, our contradictory findings demonstrate the need for further analysis and caution in using these metrics in isolation alone. Further research should seek to expand upon the models developed in this study to include other measures that may be associated with injury such as strength, power, conditioning, age, etc. These models should also consider a mechanistic framework that may connect the variables monitored to injury occurrence. Without such frameworks, these models demonstrate only associations, like ice cream sales and shark attacks.

Chapter 5: CRP analysis

The final objective of this dissertation was to use an injury framework to propose that systemic inflammation may be a mediator between higher workload ratios and non-contact injury occurrence. Our first aim of this study was to measure salivary CRP levels weekly in college football players during the pre-season and in-season periods, and to compare the fluctuations in these levels with their prior activity. We expected that there would be significant increases in CRP levels, because of increased activity, during the pre-season practice period. However, our results did not support this hypothesis. The one-way repeated measures ANOVA yielded no significant difference in CRP concentrations across time.

The second aim of this study was to assess the relationship between weekly load, workload ratios, CRP levels, and non-contact injury. Again, we expected that increased CRP levels would be found after high weekly loads and workload ratios; and that the increased CRP levels would be associated with greater non-contact injury risk. Though weekly load demonstrated a fair correlation with CRP concentration, the panel regression indicated a non-significant association. Furthermore, neither ACWR nor EWMA calculations were correlated with CRP. Ultimately our planned analyses were derailed by the occurrence of only 1 non-contact time-loss injury in our sample. The lack of injury occurrence was not due to a lack of high workload ratio values. As a result, this study supports the findings from our previous discussions, as well as the recent literature(163, 216), which highlight the need to not rely exclusively on “high” workload ratios as the sole indicator of increased injury risk.

Though these present findings do not currently support the causal link between increased activity, the resulting systemic inflammation, and subsequent non-contact injury, it is worth investigating further. C-reactive protein is one of several acute-phase inflammatory proteins that

are upregulated when muscle damage occurs(40). Other proinflammatory proteins include but are not limited to interleukin-1, interleukin-6, and tumor necrosis factor alpha. While CRP has a long half-life (19 hours), which makes it a strong candidate for measuring over several days, it may be that other inflammatory proteins are better associated with non-contact injury risk. Another possibility is that systemic inflammation is an acute response which demonstrates chronic effects only under extreme scenarios beyond the scope of normal sport training and participation. Therefore, more frequent measurements may be needed to elucidate the true relationship of these inflammatory proteins and injury.

In conclusion, the findings of the relationship between workload, workload ratios, chronic inflammation, and non-contact injury mirrored our findings from Chapters 3 and 4. Further work is needed to find if systemic inflammation is a mediator between increased activity and injury, as well what the appropriate markers and time intervals between measurements should be.

Conclusions

This dissertation provides a more thorough report of the non-contact injury rates associated with collegiate football participation by observing participation across entire calendar years. Our observations suggest that the previously unobserved winter conditioning, spring practice, and summer conditioning periods have at least as a high a non-contact time-loss injury rate as the in-season period of football participation and perhaps even greater. Sprains and strains of the hip/thigh region were the most frequently observed injuries. Given these findings, along with those of previous work, it seems that practitioners should invest time and resources into exploring ways to mitigate these injuries during the training cycle.

We also sought to provide a greater assessment of the current practice surrounding measuring workloads and calculating workload ratios, and the relationship of these metrics to non-contact injury occurrences by utilizing larger data sets, multiple teams, a potential mediating pathway, and modern statistical techniques. Our work illuminates the activity differences between the pre-season practice period and every other phase of sport participation. The high non-contact injury rates demonstrated during this period solidifies the need for further discussions around the rules and regulations governing sport participation during each phase of the year.

Our work, however, also yielded contradictory findings for the association of workload and workload ratio models to non-contact time-loss injuries. For starters, our assessment determined that the inclusion of linear weekly load and quadratic workload ratio covariates yielded best fitting models. The choice for workload ratio calculation method, as well as the use of general or team-specific datasets, did not significantly improve the models. Furthermore, these models demonstrated that workload was negatively associated with non-contact injury for each phase of training. Workload ratios, in these models, also demonstrated an inverted-U relationship, contradicting previous research. Previous research assessed the relationships between workloads and workload ratios with non-contact injury in isolation. This can provide misleading conclusions because workload is an absolute measure and does not address the rate of change, and workload ratios are a relative measure which do not provide context to the amount of work being performed. Our results suggest that the combination of these variables into a model accounts for a greater amount of unobserved variance and thus provides better interpretability. While specific to each dataset and workload ratio calculation method used in the GEE models, in general, injury probability increased with respect to workload ratio until that

ratio value reach 1.0. These findings contradict previous research which had previously deemed the workload ratio area between 0.8 and 1.3 the ideal for injury mitigation(116). Future research should use large and balanced panels in order to utilize frailty models to further assess the associations between workload, workload ratios, and injuries.

Lastly, in an effort to utilize an injury framework as the basis of quantifying workload, and to establish a mediating pathway between increased workloads and non-contact injury, we measured salivary C-reactive protein concentrations in a portion of a football team during the pre-season and in-season phases. The correlation of weekly workload and C-reactive protein levels in our study ranged wildly based on the individual ($r = -0.66$ to $+0.66$). In addition, observing only 1 time-loss non-contact injury limited the conclusions we were able to determine. It would be ideal to observe multiple markers of inflammation and muscle breakdown in many athletes across several football teams weekly, or multiple times per week, to thoroughly track the time-course changes of inflammatory responses in the body. That information, coupled with a standardized injury cataloging system, would permit greater confidence in the conclusions drawn. For now, it appears C-reactive protein levels are uncorrelated with weekly workloads.

The results of this dissertation offer several important developments to the field of sport science. First, we have provided the first report of non-contact injury rates for the winter conditioning, spring practice, and summer conditioning periods. Combined, this period incapsulates 60-75% of the total football calendar year. With this information, coaches and practitioners can begin to reflect on their current training and practice protocols and determine if changes need to be made for the health of their athletes.

Recommendations for future research

From the findings of this dissertation, we have several recommendations for further research which are discussed below.

1. Further research should seek to compile large datasets, comprised of multiple teams and spanning several full calendar years, in order to observe enough non-contact injuries to allow for complete statistical analysis to be performed. The datasets we were able to utilize were far larger than previous research in American football. However, datasets with more occurrences of non-contact injuries would permit the use of certain statistical techniques, for example logistic regressions, which in turn could provide more meaningful and predictive modeling of injury risk.
2. The sports medicine departments within collegiate football should seek to have agreed upon criteria for what is classified as sport participation, modified participation, and time-loss injury. Though this dissertation provided initial injury risk ratios for the winter conditioning, spring practice, and summer conditioning phases not previously reported, and is a major strength of our dissertation, consensus on how injuries are diagnosed and what constitutes removal from participation has not been established. These determinants of sport participation may also change based on the phase of training (winter conditioning vs in-season, etc.). This limits the usefulness of larger, multi-team datasets to produce true relationships between potential variables and the occurrence of injury.
3. Further work should be done to monitor the local and systemic inflammatory processes that occur as a result of sport training and participation, particularly after

periods of sustained inactivity and injury. Our dissertation was able to measure C-reactive protein in a small subgroup of athletes during a pre-season and in-season period. Though we found no associations between activity and subsequent C-reactive protein levels, our observation period occurred after the athletes had been training for several weeks. It may be that different markers and/or other time periods have a greater ability to demonstrate if inflammation occurs and if that inflammation is a mediator in non-contact injury occurrence.

4. Though it makes sense conceptually that increasing activity too quickly predisposes both regular people and elite athletes to higher risks of injury, condensing data to a single acute:chronic ratio value may be the simplest model but not necessarily the best fitting model, regardless of calculation method. Alternative models should be explored by future research to assess the relationship of a multitude of variables on subsequent injury. These variables could include measures of strength, speed, recovery, diet, sleep, neuromuscular firing patterns, anthropometrics, and many others.
5. One important finding of this dissertation is the observation of large and sudden increases in weekly workload between the summer conditioning and pre-season practice phases. Our data indicated an average 4-fold increase in activity when players begin pre-season practice. This increase is due to the current rules governing activity in summer and activity in pre-season practice. Summer conditioning is limited to 8 mandatory hours total per week and includes both weight training and conditioning. The pre-season practice permits 4 hours per day to be divided between practice and weight training. In addition, the summer period requires athletes be

given two days off per week, while the pre-season practice requires only one. Given the pre-season period as routinely shown to have the largest IRRs, through our research and others(133, 138), further research warrants looking into the rules governing this transition and explore if activity levels contribute to a significant increased risk of injury across multiple teams and years.

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