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Research Article

Personalized Acute: Chronic Workload Ratios for Injury Prediction in Football Athletes Using Wearable Technology

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Abstract

Tracking wearable technology to monitor the external loads of athletes in training and competition has become almost ubiquitous, particularly in professional sports. As GPS technology has evolved over the last decade, users now have a wealth of metrics available from which they can evaluate external load and, in conjunction with coaches, better inform the training process [1]. Athletes, coaches, performance, and medical teams have access to information on range of motion, accelerations, impacts, or other indicators, such as biometric markers, which, if correctly interpreted and assessed, can assist them in maximizing performance and minimizing injury risk for their athletes [2,3]. Lately, efforts have been made to improve data taken from GPS tracking devices through programming to make the handling of data faster and more accurate. As team-sport competitions are contested on an absolute basis, player-tracking data are commonly expressed utilizing player-independent training zones to evaluate the physical output or external loading of each playe [4]. Each training or competition performed has the potential for athletic injury, indicating that inappropriate workload exposure can increase injury risk.

Consequently, there has been growing support for the Acute: Chronic Workload Ratio (ACWR) to prescribe appropriate training loads [5]. In this work, three-month training datasets from three football players and five-month training datasets from two football players were used high-stress zones to calculate the ACWR of high-stress zone accelerations (4^{th}, 5^{th} & 6^{th}). The ACWR, i.e., the most recent 1-week assessment relative to the 4-week workload, was applied on a rolling daily window basis. Two different methodologies were employed in the calculation of ACWR. Firstly, ACWR was calculated utilizing the standard method of equal chronic workload weights, assuming an equal contribution every week to the chronic workload. In addition, ACWR was calculated utilizing unequal chronic workload weights, where the more recent the week, the larger its chronic workload contribution. Results apply on the X, Y, and Z axes, both for the standard and personalized zone definitions. A comparison between the ACWR quantities derived across both zone definitions and chronic workload weights was performed. Furthermore, ACWR measures were extended for the XY, XZ, and YZ planes under the personalized zones definitions. The time athletes spent in every zone per axis and plane across stress zone definitions was calculated as well. All in all, this study is part of broader research in establishing a relationship between measures of external load and mechanical stresses with the aim to shift the performance- and injury risk-related monitoring from measures of limited relevance to personalized, tissue-specific variables.

Keywords: Football; Athelets; Injury

Introduction

The increasing integration of wearable technology in sports has revolutionized the way athlete performance and training loads are monitored. This technological advancement, particularly in GPS tracking, provides a rich dataset comprising various metrics such as range of motion, accelerations, and impacts, which can be utilized by athletes, coaches, and medical teams to enhance performance while minimizing injury risks [[1]][[2]]. The focus on external load monitoring through these devices has led to a significant interest in developing methods for interpreting this data effectively.

A pivotal aspect of this monitoring is the Acute:Chronic Workload Ratio (ACWR), which serves as a framework for prescribing appropriate training loads. ACWR compares the recent workload (acute) with the workload over an extended period (chronic), thereby allowing practitioners to assess the readiness of athletes and the potential risk of injury [[5]]. The premise is that inappropriate workload exposure may elevate injury risks, making it essential to balance training intensities carefully [[5]].

Recent advancements have emphasized the necessity of personalized training zones, which take into account individual athlete characteristics, instead of relying on standard zones that may not reflect an athlete's unique training routine [[11]]. This approach aims to provide a more accurate assessment of the mechanical stresses experienced by athletes, thereby facilitating a shift from generalized monitoring to tailored, tissue-specific evaluations [[11]].

In this study, we analyze training datasets from multiple football players over several months to calculate ACWR values using standardized and personalized zone definitions. Additionally, we employ unequal chronic workload weights, which are posited better to reflect the relationship between recent workloads and injury risk [[5]]. Our findings contribute to a growing body of evidence supporting the use of personalized metrics in athletic training and injury prevention strategies, ultimately aiming to enhance athlete performance and safety [[15]][[16]].

Method

The data handled was taken from three-month training datasets from three football players and five-month training datasets from two football players. In order to do this, Python 3.8 was used. For the implementation, NumPy [6], Pandas [7], Matplotlib [8], Sklearn [9] and other libraries were utilized from the Python environment. The datasets contained 17 columns and included the Player's name, Time, Speed, Acceleration, and different quantities. More specifically, the focus was placed on the columns of the per-axis acceleration data fields; "AcclX," "AcclY," and "AcclZ." The acceleration data was aggregated to the one-tenth, by merging every ten rows (ten different records changing by the one-hundredth of a second) into one, taking the mean attribute values. By comparing the shape of the histograms of the variables before and after the aggregation process, it was determined that no information loss occurred.

In the following section, the three basic pillars of our analysis are described:

Standard zones for accelerations

Training zones are used to give athletes a set intensity at which they should be working during an activity to avoid injuries and perform better[4]. At present, most of the scientific work around training zones handles them as specific values, as can be seen in the table below (Table 1):

Zones	1st zone (m/s^2)	2nd zone (m/s^2)	3rd zone (m/s^2)	4th zone (m/s^2)	5th zone (m/s^2)	6th zone (m/s^2)
Values	0.5-1	1-2	2-3	3-4	4-5	5-10

Table 1: Typical acceleration zones as presented in the STATSports metric book [10].

Based on Table 1 and the standard methodology, each player's acceleration data was segmented into six training zones across axes.

Calculation of personalized zones for accelerations

A vital component of the analysis design described in this paper is the usage of personalized stress zones that were derived as follows. Across each player and axis, the distribution of the absolute values of accelerations was approximated by the distribution that minimized the Kolmogorov-Smirnov test statistic [11], a non-parametric statistical test of the equality of continuous one-dimensional distributions (83 different distributions were utilized). Demarcation of the personalized training zones was conducted by dividing the Cumulative Distribution Function (CDF) [12] of the optimal distribution into six equal segments (1/6, 2/6, 3/6, 4/6, and 5/6 percentiles).

Therefore, personalized zones are not pre-set theoretically, arbitrarily, and independently of any player characteristics (e.g., age, fitness levels, and more). Instead, they represent actual and "visitable" ranges across each player's training routine. (Table 2) contains the personalized zones for the X-axis accelerations for all players.

Players	1st zone (m/s^2)	2nd zone (m/s^2)	3rd zone (m/s^2)	4th zone (m/s^2)	5th zone (m/s^2)	6th zone (m/s^2)	Optimal Distribution
Player1	0-0.05	0.05-0.10	0.10-0.15	0.15-0.22	0.22-0.35	0.35-4.84	fatiguelife
Player2	0-0.04	0.04-0.09	0.09-0.15	0.15-0.21	0.21-0.32	0.32-10.93	mielke
Player3	0-0.03	0.03-0.07	0.07-0.11	0.11-0.17	0.17-0.29	0.29-14.92	mielke
Player4	0-0.05	0.05-0.09	0.09-0.13	0.13-0.20	0.20-0.35	0.35-5.42	inverse gamma
Player5	0-0.04	0.04-0.08	0.08-0.13	0.13-0.19	0.19-0.30	0.30-4.52	mielke

Table 2: Personalized zone thresholds for the acceleration across the X-axis for all players.

Indeed, as Table 2 shows, the maximum acceleration across the X-axis for Players 1 and 5 is lower than 5 m/s^2. Consequently, according to Table 1, these two players have no observations in Zone 6 as per the standardized stress zone definition.

(Table 3 and Table 4) depict the time spent in each zone along the X-axis, across both zone definitions, for all players. As can be seen from the tables, the time spent in high-stress zones under the standardized zone definitions is minimal. On the other hand, utilizing the personalized zones definition approach, the time spent in each zone is roughly equally distributed. The better the fit of the optimal distribution to the data, the closer the distribution of time allocated in the personalized zones will be to the distinct Uniform distribution of probability 1/6 (Table 3,4).

Players	1st zone	2nd zone	3rd zone	4th zone	5th zone	6th zone
Player1	99.274%	0.6972%	0.0276%	0.0011%	0.0004%	0.0000%
Player2	99.176%	0.7938%	0.0277%	0.0017%	0.0003%	0.0004%
Player3	99.205%	0.7495%	0.0360%	0.0038%	0.0019%	0.0038%
Player4	98.588%	1.2015%	0.1925%	0.0173%	0.0006%	0.0001%
Player5	99.216%	0.7187%	0.0553%	0.0099%	0.0001%	0.0000%

Table 3: Distribution of time spent in standardized zones for the acceleration across the X-axis.

Players	1st zone	2nd zone	3rd zone	4th zone	5th zone	6th zone
Player1	17.211%	14.301%	16.082%	16.904%	22.167%	13.335%
Player2	16.281%	16.586%	16.263%	17.135%	17.482%	16.253%
Player3	15.316%	15.024%	17.004%	18.636%	19.263%	14.758%
Player4	18.329%	14.367%	15.072%	16.640%	19.172%	16.420%
Player5	16.586%	16.954%	16.855%	16.304%	16.563%	16.737%

Table 4: Distribution of time spent in personalized zones for the acceleration across the X-axis.

Therefore, observing Tables 2, 3, and 4, the need for player-dependent zone ranges that reflect the players' actual training routine becomes evident.

(Table 5) depicts the pair-wise Pearson and Spearman correlations [13] of the acceleration across different axes. A noticeable correlation emerged, and in order to further pursue it, the analysis was extended to the XY, XZ, and YZ planes as well. To begin with, three new quantities, "AcclXY", "AcclXZ" and "AcclYZ", were defined. The acceleration values across each plane were defined as the product of the accelerations of the axes that define them (e.g. each data point of "AcclXY" was defined as the product of the corresponding data points of "AcclX" and "AcclY"). Consequently, based on these new "accelerations" defined on the planes XY, XZ and YZ, respectively, each player's personalized zones was calculated using the same methodology described above. Finally, the distribution of time spent per plane in each personalized zone was calculated and presented in the corresponding results section.

Players	Pearson (X, Y)	Spearman (X, Y)	Pearson (Y, Z)	Spearman (Y, Z)	Pearson (Z, X)	Spearman (Z, X)
Player1	84.81%	86.77%	68.48%	78.41%	36.04%	59.44%
Player2	94.44%	85.81%	98.21%	94.69%	94.51%	86.01%
Player3	86.87%	84.54%	98.00%	97.96%	80.61%	79.88%
Player4	45.90%	51.05%	98.56%	97.85%	46.03%	50.13%
Player5	81.83%	90.49%	97.84%	98.53%	85.47%	93.06%
Average	78.77%	79.73%	92.22%	93.49%	68.53%	73.70%
Median	84.81%	85.81%	98.00%	97.85%	80.61%	79.88%

Table 5: Pair-wise Pearson and Spearman correlations for the pairwise accelerations across axes.

Calculation of ACWR

The computation of ACWR involves the assessment of the absolute 1-week workload (acute workload) relative to the 4-week chronic workload (4-week acute workload)[5]. This ratio was calculated on a rolling daily window basis. Therefore, based on the derived standardized and personalized zones across axes and planes, the ACWR for the high-stress zone accelerations (4^{th}-6^{th} zone) was calculated. More specifically, the acute workload (numerator) was calculated as the sum of accelerations on the 4^{th} – 6^{th} zone of the most current week. The chronic workload (denominator) was calculated as the weighted average of the sum of accelerations on the 4^{th} – 6^{th} zone of the measured week and its previous three weeks. A particular focus was placed on the 4^{th} to the 6^{th} zones as these are the high-stress zones where our interest lies, given that most injuries happen under stressful conditions. The evolution of the ACWR time series can be formulated for day-t as follows:

$$ACWR_t = \frac{(S_t + S_{t-1} + S_{t-2} + S_{t-3} + S_{t-4} + S_{t-5} + S_{t-6})}{w_1(S_t + \cdots + S_{t-6}) + w_2(S_{t-7} + \cdots + S_{t-13}) + w_3(S_{t-14} + \ldots + S_{t-21}) + w_4(S_{t-21} + \cdots + S_{t-28})}$$

Where S_t is the sum of the high stress zones accelerations (4^{th}-6^{th}) for day t and $w_{i,}$ are the chronic workload weights. Each weight is assigned to a different week such that:

- $w_i \ni (0,1), \forall i = 1, \ldots 4 w_i \ni (0,1), \forall i = 1, \ldots 4$
- $\sum_{i=1}^{4} w_i = 1 \sum_{i=1}^{4} w_i = 1$

The following should be noted:

- ACWR was calculated on a daily rolling-window basis instead of weekly, which is the standard practice.
- ACWR can be defined across all axes and planes.
- ACWR can be defined across both stress zone definitions.
- ACWR can be defined across all possible chronic workload weights.

Two different sets of weighting methodologies (w_1, w_2, w_3 & w_4) were utilized; equal and unequal. The former method is the original formulation of ACWR, and it is widely used according to standard practice. The latter methodology was employed mainly because an injury is more likely to be associated with the most recent workload than with the workload performed weeks prior. These results emerged from a choice of weights such that $w_1 > w_2 > w_3 > w_4$. More specifically, after conducting an appropriate analysis, the choice of weights was the following: $w_1=0.4$, $w_2=0.3$, $w_3=0.2$, and $w_4=0.1$.

Finally, observing Table 3, it should be noted that under the standardized stress zone definition, only a tiny percentage of observations (less than 0.02%) would be used to calculate ACWR. These observations could be outliers or measurement errors and do not represent the actual range of high-stress acceleration values of the athletes. Therefore, making inferences based on a metric that has been calculated utilizing such a small sample of the available data would lead to results that are player-agnostic and potentially erroneous.

State of the Art

Workload-injury investigations in team sports typically quantify workload in absolute terms (e.g., the workload performed in a week vs injury). Accepting that high absolute training loads are associated with greater injury risk, strength, and conditioning practitioners must also consider how week-to-week changes in training load independently influence injury risk (aside from total training load). Indeed, Tim Gabbett, in 2016, stated that there is a benefit in modeling the training–injury relationship using a combination of both acute and chronic training loads. Acute training loads can be as short as one session, but in team sports, one week of training appears logical and convenient. Chronic training loads represent the rolling average of the most recent 3–6 weeks of training. In this respect, chronic training loads are analogous to a state of ‘fitness’, and acute training loads are analogous to a state of ‘fatigue’. Comparing the acute training load to the chronic training load as a ratio provides an index of athlete preparedness [14].

From the above point of view, usual workload-performance investigations have examined absolute workload performed in 1 week (referred to as acute workload) relative to 4-week chronic workload (i.e., 4-week acute workload). The logic behind this comparison of workloads is the provision of a workload index, which indicates whether the athlete’s recent acute workload is more significant, less than, or equal to the workload that the athlete has been prepared for during the preceding chronic period. We refer to this method demonstrated by research findings that provides a better prediction of injury than absolute workload in isolation, as the acute: chronic workload ratio [15]. Providing evidence around the effects of acute and chronic training load on injury risk, physical fitness, and performance will allow practitioners to systematically prescribe high training loads while minimizing the risk of athletes sustaining a ‘load-related’ injury. The ACWR model is evidence-based and considered a best-practice approach for modeling the relationship between load and injury across various sports.

In the original formulation of the ACWR, the chronic load is defined as the weekly average of the workload performed in the past four weeks. Each of the four weeks is weighted equally in the calculation. While straightforward to calculate, the equal weighting obscures weekly variations in activity load and neglects the effects of training decay over time. The underlying issue is that an injury is typically more likely to be associated with one’s most recent workload than the workload performed weeks prior. To solve this problem, some authors suggested various ways of approaching it, such as different weights per week or even exponentially weighted moving averages [13]. This paper calculates average workloads by providing more weight to recent workloads and less weight to workloads in the distant past [17-27].

Results

This section summarizes the results of the ACWR analysis described (Figures 1-12).

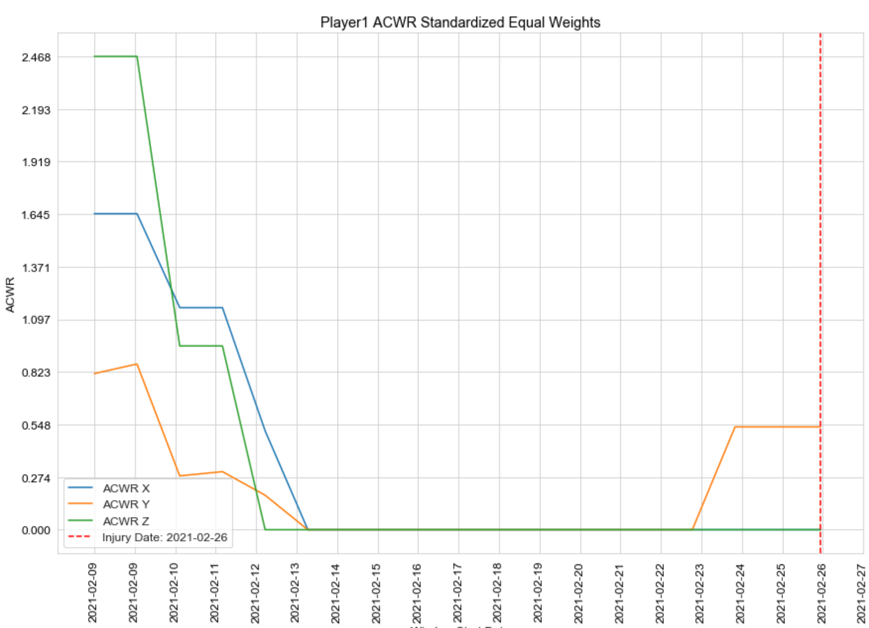

Figure 1: ACWR of Player 1 along the axes using the standardized zones definition and equal chronic workload weights.

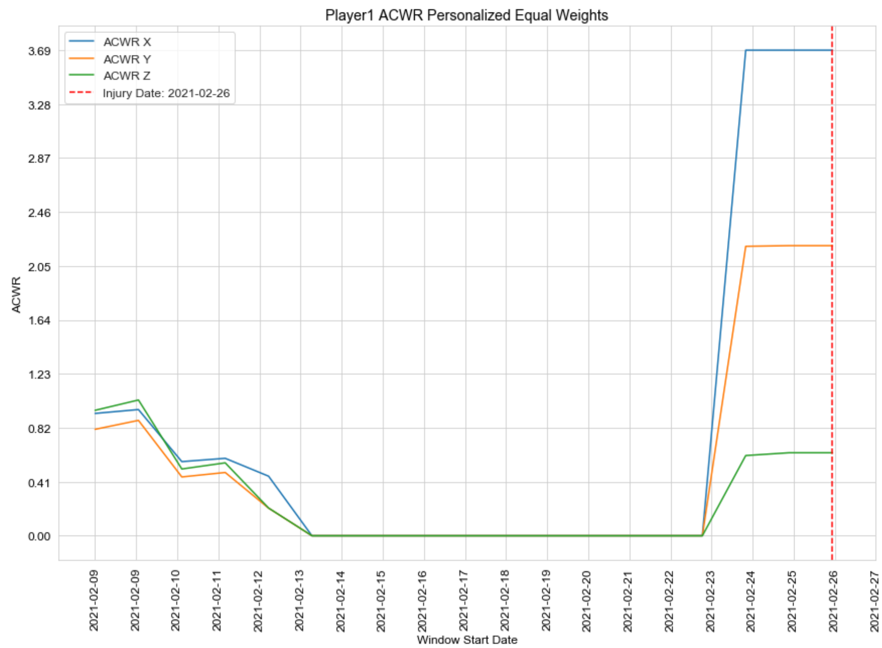

Figure 2: ACWR of Player 1 along the axes using the personalized zones definition and equal workload weights.

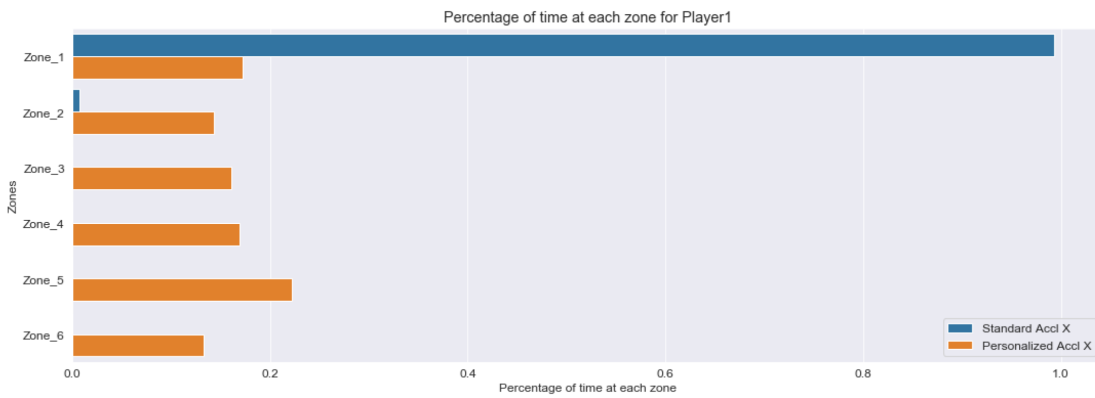

Figure 3: Distribution of the total time spent in each zone, across both zone definitions, for Player 1 along the x-axis.

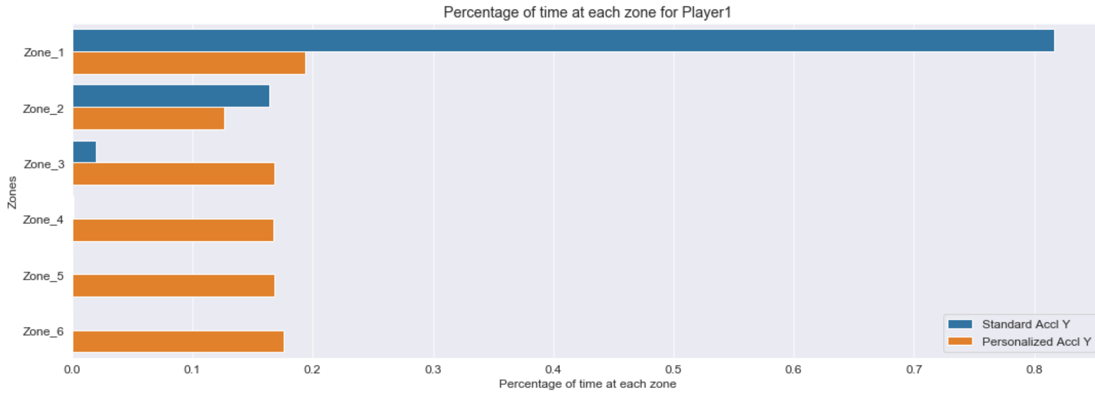

Figure 4: Distribution of the total time spent in each zone, across both zone definitions, for Player 1 along the y-axis.

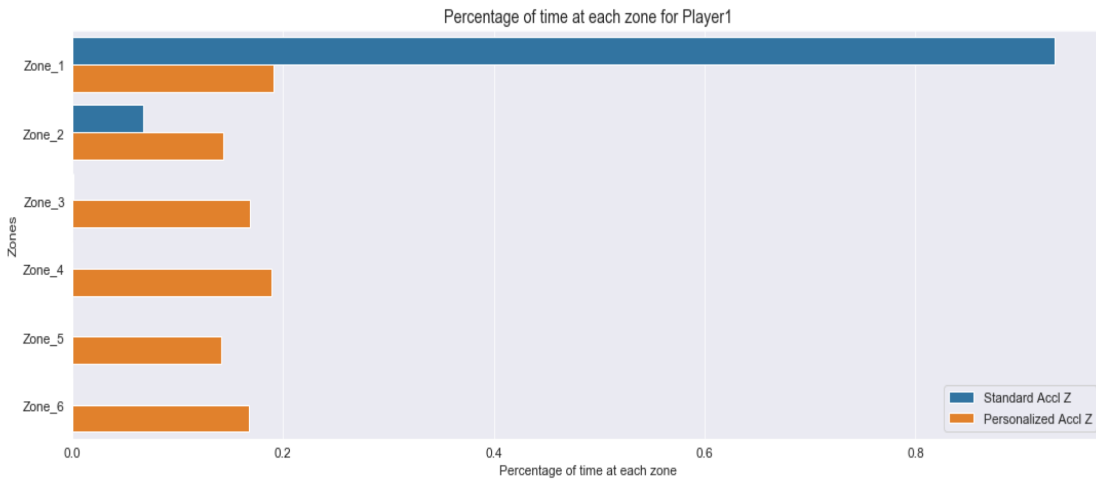

Figure 5: Distribution of the total time spent in each zone, across both zone definitions, for Player 1 along the z-axis.

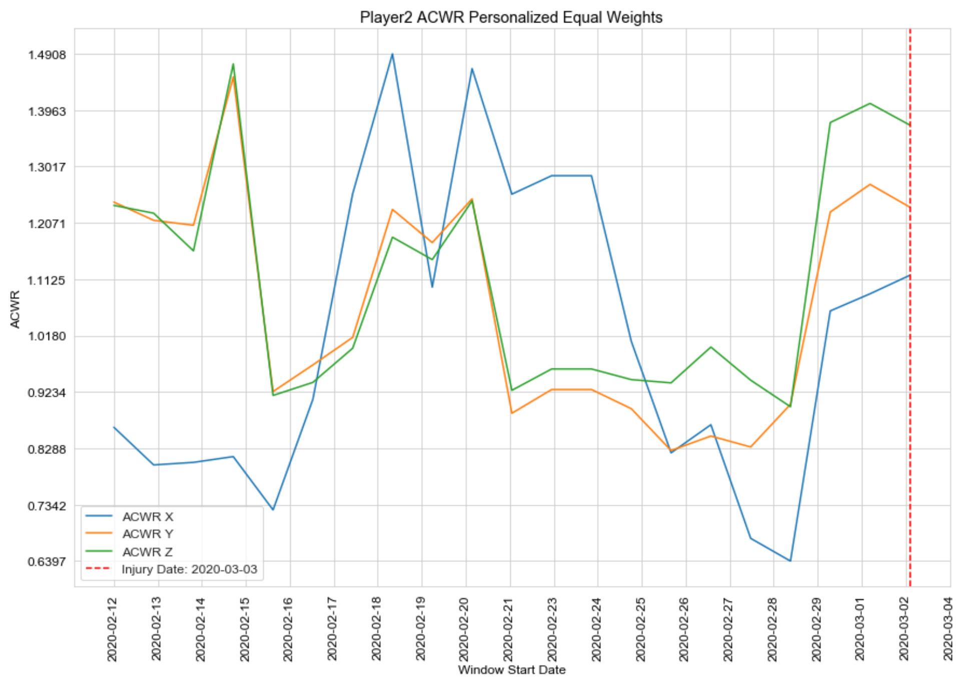

Figure 6: ACWR of Player 2 along the axes using the personalized zones definition and equal chronic workload weights.

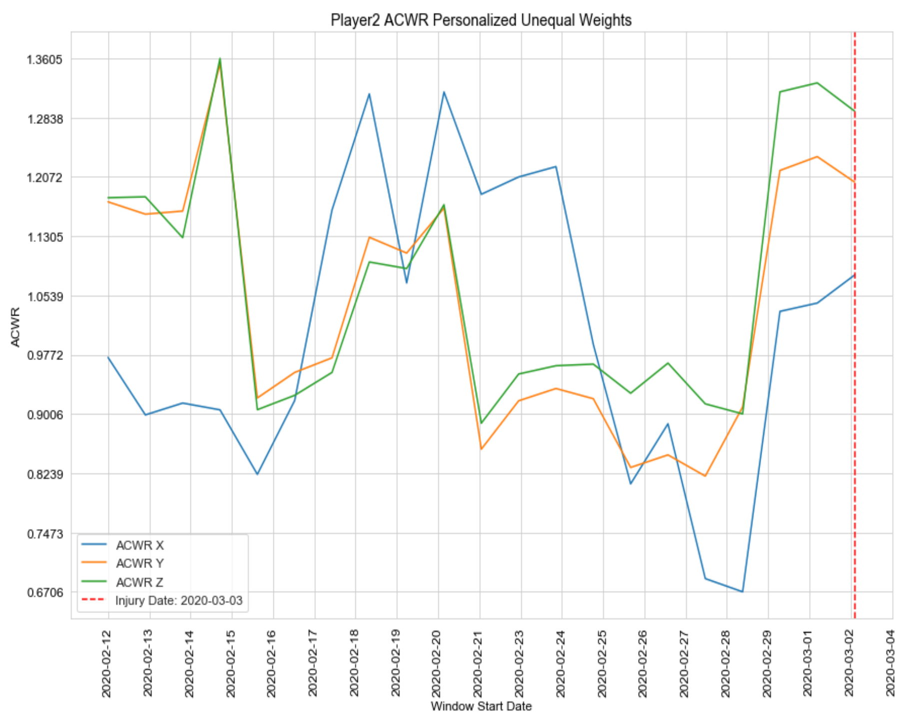

Figure 7: ACWR of Player 2 along axes using the personalized zones definition and unequal chronic workload weights.

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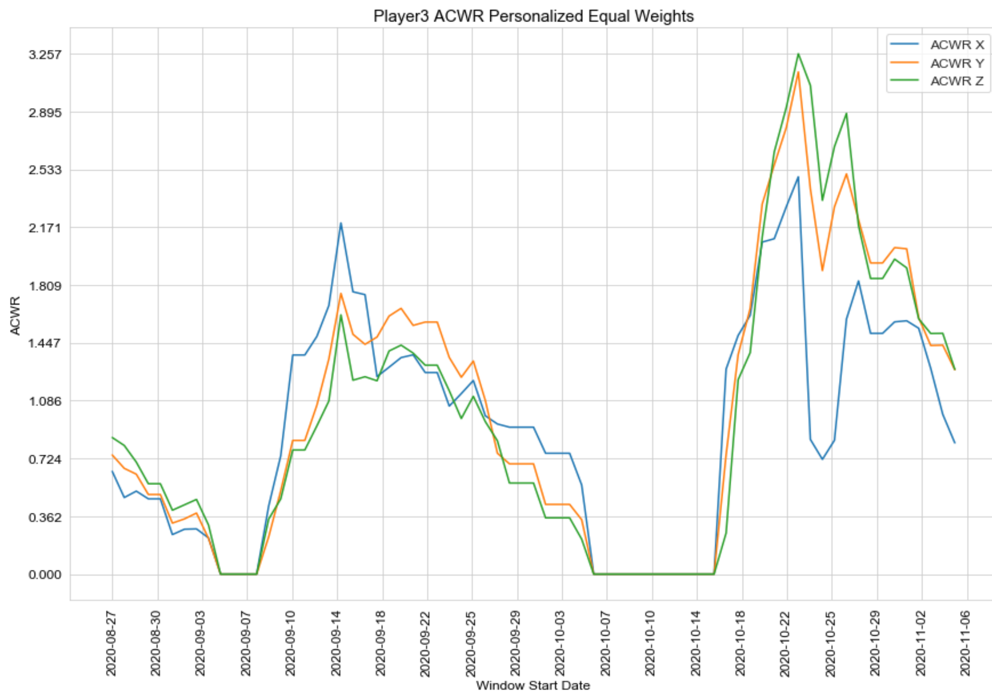

Figure 8: ACWR of Player 3 along axes using the personalized zones definition and equal chronic workload weights.

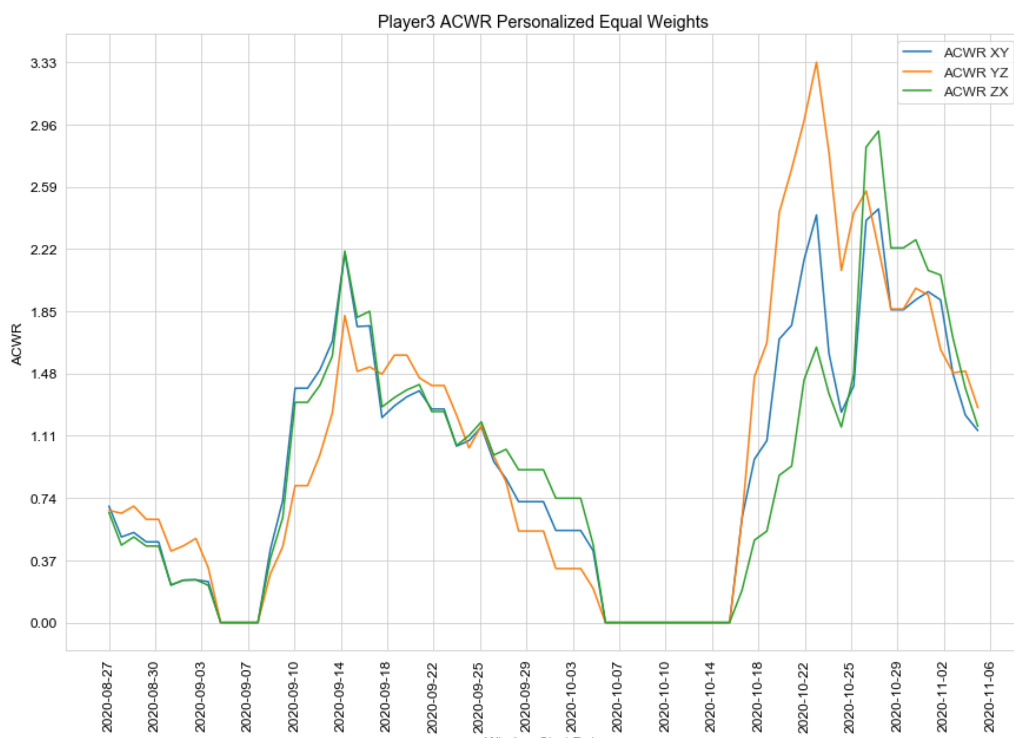

Figure 9: ACWR of Player 3 along planes using the personalized zones definition and equal chronic workload weights.

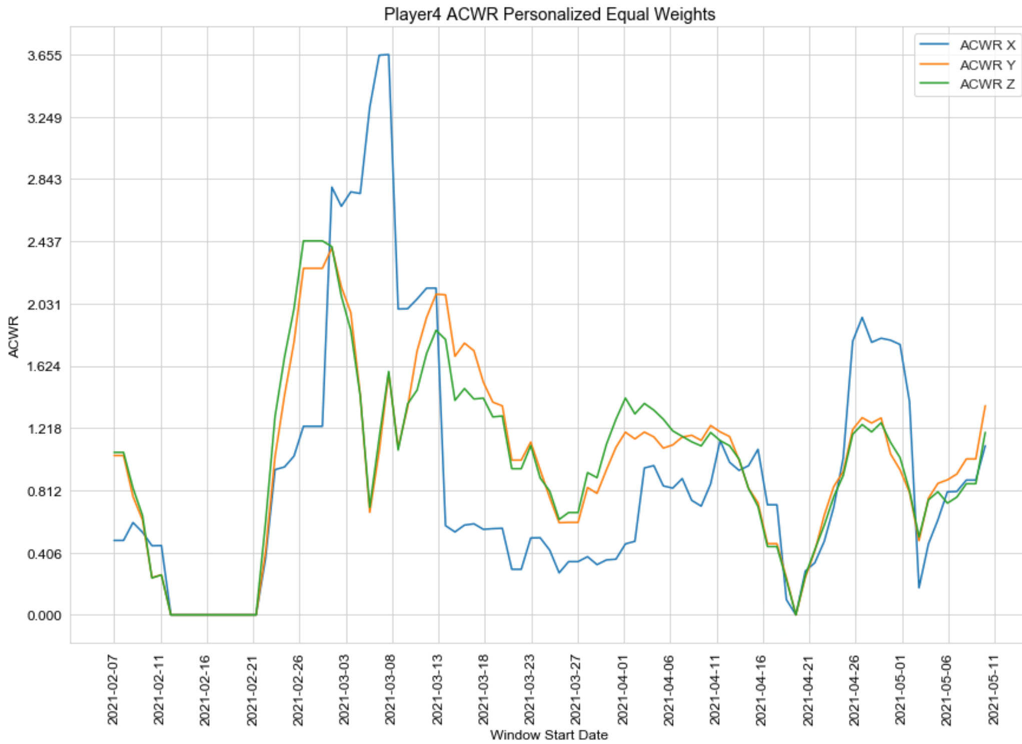

Figure 10: ACWR of Player 4 along axes using personalized zones and equal chronic workload weights.

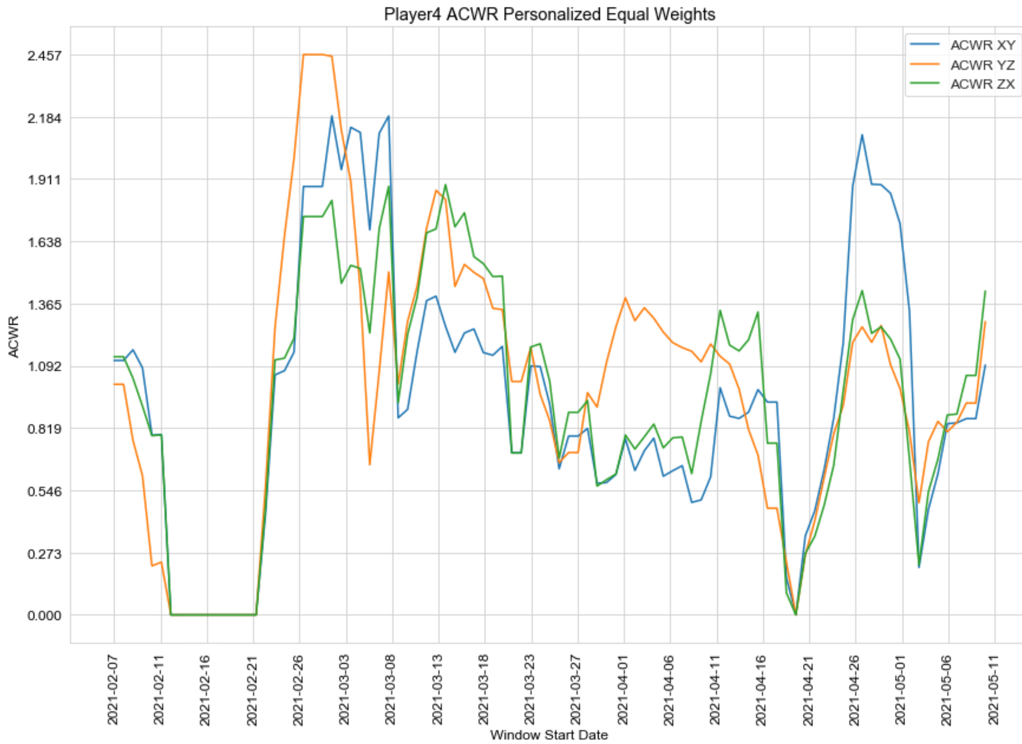

Figure 11: ACWR of Player 4 along planes using personalized zones and equal chronic workload weights.

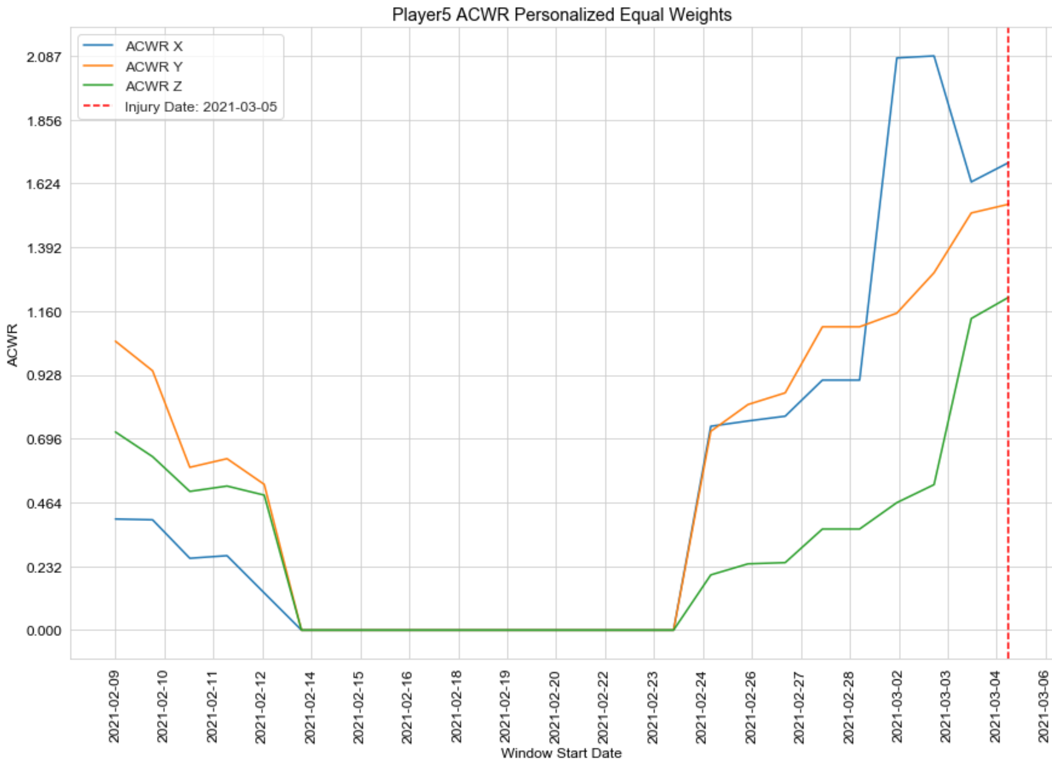

Figure 12: ACWR of Player 5 along axes using personalized zones and equal chronic workload weights.

Discussion

This study aims to provide insights in injury prediction utilizing the ACWR, while also demonstrating the observable differences between the different ACWR measures discussed. The following points were noted:

- Observing Figure 1, it can be seen that only the y-axis somewhat captures the sudden increase in ACWR, which ultimately provides a sign for the athlete's imminent injury. On the other hand, in Figure 2, the ACWR calculated utilizing the personalized stress zone definition offers a more discernible pre-injury pattern across all axes.

- Observing Figure 6 and Figure 7, it can be deduced that using different chronic workload weights does not seem to lead to significant deviations in the ACWR patterns.

- As previously mentioned, the ACWR time series of the accelerations along the planes XY, YZ, and XZ is derived through the products of the ACWR time series of the accelerations along the corresponding axes. Observing Figure 8 & Figure 9 as well as Figure 10 & Figure 11, it can be seen that the ACWR patterns of accelerations between planes and axes does not seem to lead to significant differences. The main reason is that the ACWR figures across axes follow the same pattern, leading to similar patterns in their corresponding pair-wise products. This can also be confirmed by the high pair-wise Pearson and Spearman correlations between axes depicted in Table 5.

- Finally, utilizing Figure 2, Figure 6, and Figure 12, discernible pre-injury patterns and signals emerge from the equally weighted personalized ACWR figures along the axes. Indeed, in all 3 cases, there is a considerable and sudden spike followed by a fall of less magnitude, followed by an upward trend where the injury ultimately occurs. The physical meaning behind these patterns is the following: when a player in a short period has a very intense schedule (increased high stress zone workload), then reduces the workload pace for a short time and then continues for another increased workload schedule, an injury pattern emerges. The figures mentioned above show that the injury occurs at most five days away from the first and largest spike.

All things considered, the incorporation of the personalized stress zone approach in load monitoring resulted in ACWR patterns that seem to have the potential to detect signals that could be used for injury prediction purposes.

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