3-31-2021

Relationships between internal training load in a taper with elite weightlifting performance calculated using different moving average methods

Joseph O. C. Coyne
Edith Cowan University

Robert U. Newton
Edith Cowan University

G. Gregory Haff
Edith Cowan University

10.1123/IJSPP.2020-0002
Accepted author manuscript version reprinted, by permission, from International Journal of Sports Physiology and Performance, 2021, 16(3): 342-352, https://doi.org/10.1123/ijspp.2020-0002. © Human Kinetics, Inc.
Coyne, J. O. C., Newton, R. U., & Haff, G. G. (2021). Relationships between internal training load in a taper with elite weightlifting performance calculated using different moving average methods. *International Journal of Sports Physiology and Performance, 16*(3), 342-352. https://doi.org/10.1123/IJSPP.2020-0002

Relationships Between Internal Training Load In a Taper with Elite Weightlifting Performance Calculated Using Different Moving Average Methods

Journal:	*International Journal of Sports Physiology and Performance*
Manuscript ID	IJSPP.2020-0002.R1
Manuscript Type:	Original Investigation
Date Submitted by the Author:	14-Mar-2020

Complete List of Authors:	Coyne, Joseph; Edith Cowan University, Centre for Exercise and Sports Science Research Newton, Robert; Edith Cowan University, Centre for Exercise and Sports Science Research Haff, G.; Edith Cowan University, Centre for Exercise and Sports Science Research; Salford Univeristy, Directorate of Sport, Exercise, and Physiotherapy

Keywords:	Monitoring, Simple Moving Average, Exponentially Weighted Moving Average, Periodization, Acute to Chronic Workload Ratio

Relationships Between Internal Training Load In a Taper with Elite Weightlifting Performance Calculated Using Different Moving Average Methods

ABSTRACT

Purpose: A simple and two different exponentially weighted moving average methods were used to investigate the relationships between internal training load (TL) and elite weightlifting performance. ***Methods***: Training impulse data (sessional ratings of perceived exertion * training duration) were collected from 21 elite weightlifters (age 26.0 ± 3.2 years, height 162.2 ± 11.3 cm, body mass 72.2 ± 23.8 kg, previous 12 month personal best total 96.3 ± 2.7% of world record total) during the eight weeks prior to the 2016 Olympic Games qualifying competition. The amount of training modified or cancelled due to injury/illness was also collected. Training stress balance (TSB) and acute to chronic workload ratio (ACWR) were calculated with the three moving average methods. Along with the amount of modified training, TSB and ACWR across the moving average methods were then examined for their relationship to competitive performance. ***Results:*** There were no consistent associations between performance and TL on the day of competition. The volatility (standard deviation) of the ACWR in the last 21 days preceding competition was moderately correlated with performance across moving average methods (r=-0.41-0.48, p=0.03-0.07). TSB and ACWR volatility in the last 21 days were also significantly lower for successful performers but only as a simple moving average (p=0.03 and 0.03, g=1.15 and 1.07 respectively). ***Conclusions***: Practitioners should consider restricting change and volatility in an athlete's TSB or ACWR in the last 21 days prior to a major competition. Additionally, a simple moving average seemed to better explain elite weightlifting performance compared to the exponentially weighted moving averages in this investigation.

KEYWORDS

Monitoring, Simple Moving Average, Exponentially Weighted Moving Average, Periodization, Acute to Chronic Workload Ratio

INTRODUCTION

Training load (TL) monitoring is an associated extension of periodization theory.[1] In practice, methods of monitoring TL can vary considerably depending on the type of sport or activity.[2] Despite this, TL models are commonly computed using training impulse data[2,3], which is calculated as a product of an intensity factor multiplied by a volume/duration factor.[3] An athlete's overall response to training is then modelled as the difference between "fitness" (positive) and "fatigue" (negative) functions.[2,3] Popular simplified extensions of this model has been the development of training stress balance (TSB) and the acute to chronic workload ratio (ACWR).[4,5] These have been calculated using the difference (TSB) or ratio (ACWR) between the simple moving (rolling) averages of TL over acute and chronic periods.[4,5]

Training load can be described as either internal or external and it is recommended that both these constructs are used to assess the training process.[6,7] There are a number of external TL measures that are common in weightlifting e.g. volume load.[8,9] The use of internal TL measures such as sessional ratings of perceived exertion (sRPE) in weightlifting remain contentious despite recommendations as a primary TL measure[10,11] and its common use in endurance sports.[2] Theoretically, sRPE accounts for the perception of physiological, biomechanical and mental work an athlete completes and any influence of environmental factors inside and outside of training[7] and may be a useful complement for external TL in weightlifting. There appears to be relationships with sRPE and performance in both open (Australian Rules football)[12-14] and closed skill sports (sprinting and distance running).[15-17] However, the evidence for this relationship with performance has been presented with a number of different TL derivatives e.g. ACWR, TSB, strain, monotony. One major difference between these variables is that monotony and strain are products of the TL standard deviation.[18] Although relationships with performance have not seemed to be examined, previous athlete monitoring research using monotony has suggested relatively less negative training outcomes (i.e. illness) if the TL standard deviation is higher when compared to the weekly TL.[18,19] This is notable considering the standard deviation of time series data is considered important in other industries that specialize in forecasting and risk assessment like the financial markets.[20] For instance, in financial analysis, greater volatility of an asset may indicate a greater risk in and higher or lower prices for buying and selling the asset or options for the asset.[20] The time series' standard deviation is commonly referred to as volatility in the financial industry[20] and this term will be used throughout the remainder of the paper.

There has been debate about the most appropriate moving average methods used to determine acute and chronic TL.[21,22] It is theorised that simple moving averages (SMA) may not account for variations in how TL is accumulated by athletes nor best represent the physiological gain or decay of "fitness" and "fatigue".[21,22] Exponentially weighted moving averages (EWMA) have been recommended as a superior alternative.[21-23] However, like SMA, there are also conceptual issues with EWMA.[7] For instance, the set time constants used with EWMA calculations may be problematic as athletes will have individual "fitness" and "fatigue" gain and decay rates.[7] Additionally, there have also been several different EWMA calculations presented in the scientific literature.[14,21] All three of the different calculation methods produce different TL values for acute and chronic periods and it is unclear whether one has a superior relationship to performance. Further debate has also been raised over the use of the ACWR with the main criticism being that the ratio produces a spurious correlation due to mathematical coupling i.e. the numerator (acute TL) is contained in the denominator (chronic TL).[24] However recent publications suggest that any correlations between acute and chronic TL in the ratio may not necessarily be spurious (i.e. misleading) or may be practically unrelated to ACWR's relationships with other factors e.g. injury risk.[25,26] Nevertheless, TSB (as it is the difference rather than the ratio between acute and chronic loads) may be preferred over the ACWR for practitioners concerned with these issues.

In light of the potential benefits of using sRPE as a method for quantifying TL and the low level of current evidence supporting potential relationships between sRPE and performance in closed skilled sports like weightlifting, further investigation in this area is warranted. As such, the first two aims of this study are to: i) examine whether TL variables were correlated to the performance of elite weightlifters; and ii) determine if meaningful differences existed in the TL variables between higher and lower performers. It was hypothesized that there would be a significant correlation in TL variables with performance along with significant differences between higher and lower performers. The third aim of the investigation was to compare if there was any effect of moving average methods on the statistical analysis. The authors hypothesized that TL derivatives calculated using EWMA would have a greater correlation to performance and better separate higher and lower performing groups than a simple moving average.

METHODS

Subjects

Twenty-eight elite male (n=13) and female (n=15) weightlifters (26.0 ± 3.2 years, 162.2 ± 11.3 cm, 72.2 ± 23.8 kg, previous 12 month personal best total 96.3 ± 2.7% of world record total) from the same national team participated in this 8-week study. The subjects competed across the full range of male and female weight classes in the 2016 Olympic Games (54kg-+105kg male, 48kg-+75kg female). Seven subjects were excluded from analysis due to issues with data collection compliance (n=3; all male) or failing to post a competition total i.e. a successful lift in both snatch and clean & jerk (n=4; 3 female and 1 male). The data for this study were initially collected within the athletes' training environment and was released de-identified from the respective National Olympic Committee in this university approved retrospective study. Approval for this investigation was granted by the University Human Ethics Committee (Approval #19521) and conforms to the *Code of Ethics of the World Medical Association* (Declaration of Helsinki).

Design

This investigation was a retrospective observational study design. Internal TL data (sRPE and training duration) were collected from elite weightlifters during the last 8 weeks prior to a major competition that was critical to selection for the 2016 Olympic Games. Illness or injury incidents that caused an athlete to modify technical training or seek medical attention were noted throughout the 8-week training period.[27] The correlations between acute TL, chronic TL, TSB, ACWR, %INJ and competitive performance were examined.

Differences in these TL variables between higher and lower performers and top five and bottom five performers were also investigated.

Methodology

After athlete instruction and familiarisation, sRPE were recorded with the 10-point category ratio scale (CR10) 30-120 minutes after each session[28,29] for the total training session (i.e. technical and non-technical exercises). The sRPE were then multiplied by the total session duration to give training impulse. The following variables were calculated daily from the training impulse data: i) acute TL (7 day average); ii) chronic TL (21 day average); iii) TSB (chronic - acute TL); and iv) ACWR (acute/chronic TL) using established methods[2]. These variables were calculated with SMA, EWMA as per Williams et al (EWMA-W)[21] and EWMA as per Lazarus et al (EWMA-L)[14]) to establish if there was any effect of moving average method on the statistical analysis. These three moving average methods were chosen for analysis as, at least to the author's knowledge, they have been the prevalent methods presented or suggested in literature on TL monitoring.[2,14,21] In regard to the differences between the two EWMA calculations used in this study, the primary difference is the time constant component in the calculation. EWMA-W uses 2/N+1 as the time constant whereas EWMA-L uses 1/N with N representing the number of days.[14,21] EWMA-L has been suggested to be a superior alternative to EWMA-W as it gives a weighted average that has the highest correlation with the SMA of time constant days.[14] For example, the 10-day EWMA-L would have the highest correlation with a 10-day SMA and lower correlations with 7 and 14 days. However, to the best of the author's knowledge, the two EWMA methods have not been compared with one another with a variable of interest (i.e. performance) and it is debatable as to which one is most appropriate for calculating TL.

The acute and chronic periods were set at 7:21 days respectively. The determination of period lengths were based on an average fitness time decay constant of 23.2 days in previous research on elite weightlifters.[30] The period length determination was also based on the typical training micro-mesocycle combination used by the weightlifting athletes in this investigation.[7] This was typically a three-week mesocycle with a "moderate, "hard", "easy" loading pattern; although there were differences in how technical coaches applied this with individual athletes. Microcycles were generally comprised of two training sessions/day alternated with one training session/day for the first 6 days of the microcycle and a complete rest day on the 7th day. Commonly athletes would perform weightlifting technical exercises (e.g. snatch, clean, jerk) followed by strength exercises (e.g. squat, deadlift) and assistance or hypertrophy exercises (e.g. pull ups, lower back exercises) in each training session. Based on exploratory data analysis, acute TL, chronic TL, TSB and the ACWR were then assessed as: i) absolute values, which represented the value on the day of the competition; ii) the value 21 days prior to competition subtracted from the value on the day of the competition (CHANGE21); and iii) the volatility (calculated as the standard deviation) of values in the last 21 days prior to competition (VOL21).

The last 21 days prior to competition was chosen for the time period of interest based on the results of existing performance modelling research, tapering research and typical taper length of the weightlifting athletes in this investigation.[30,31] The percentage of modified training due to injury/illness compared to total training time was also considered in the last 6 weeks before competition.[27] This percentage of training was based on any injury or illness that affected an athlete's training (e.g. a shoulder injury may have limited exercise choice or volume for coaches) or required medical intervention. TL and injury/illness variables were then compared against competition performance results. Performance was defined as the competition results expressed as a percentage of previous 12-month personal best and of the current world record at time of competition from the weightlifters that successfully completed a repetition in both lifts. Athletes were then divided into successful and non-successful groups (n=10 and 8 respectively) and top five and bottom five performance groups. The allocation into either the successful or non-successful groups was determined by whether the athlete produced a competition performance result as percentage of previous 12-month personal best greater or lesser than the smallest worthwhile change threshold. The smallest worthwhile change threshold was defined as 0.2 x standard deviation of complete cohort competition results.[32] Meanwhile, the top 5 competition performance results as percentage of previous 12-month personal best were allocated to the top five performance group and the bottom 5 competition performance results were allocated to the bottom 5 performance group. There were 3 athletes from the cohort who were not allocated to either group as their competitive results fell inside this threshold.

Statistical Analysis

Statistical analyses were performed using statistical software (R statistics package, https://www.r-project.org) or purposefully designed Excel spreadsheets (Microsoft Corporation, Washington, U.S.). All data were analysed as mean ± standard deviation (SD). Pearson's correlation analyses with 95% confidence intervals were used to determine if there were any linear relationships between the TL variables calculated with the different moving average methods and competition performance and also between percentage of total training modified due to injury and illness and competition performance. R-z transformations were also applied to determine if there were any significant differences between correlations with performance amongst the various moving average methods. Differences between groups were expressed relative to the total cohort as a beta percentage (e.g. successful group – non-successful group / total cohort) to account for subjects within the smallest worthwhile change thresholds and the national team's normal training practice. If the different groups' TL and injury/illness variables were normally distributed, an independent student's t-test or Welch's t-test was used based on F-test results. If the different groups' TL and injury/illness variables were not normally distributed, log transformation of the particular variable[32] and visual inspection of log-transformed QQ plots were applied before using the appropriate t-test based on variance testing. Outliers were inspected and were excluded only if they were results of errors in data collection. The alpha level for significance was defined as $p \leq 0.05$. For normally distributed variable comparison, effect sizes (Hedge's g) were also calculated and interpreted. If variable data were non-normal, the difference between the two log-transformed values were converted to Hedge's g for comparison.[33] These effect sizes were then interpreted as per the recommendations of Hopkins et al with g <0.19 defined as trivial, 0.2-0.59 as small, 0.6-1.19 as moderate, 1.2-1.99 as large and >2 as very large.[32]

Cumming estimation plots were also applied to help visualize differences between groups.[34] In these plots, the raw data is plotted on the upper axes and each mean difference is plotted on the lower axes as a bootstrap sampling distribution. Mean differences are depicted as dots and 95% confidence intervals are indicated by the ends of vertical error bars.

RESULTS

A total of 1278 training sessions were included in the present analysis. The subject's competition results as percentages of previous 12-month personal best and of the current world record at time of competition along with percentage of total training modified due to injury and illness are presented in Table 1.

TABLE 1 ABOUT HERE

The average TSB and ACWR were 20.1 ± 82.1 and 0.93 ± 0.26 (SMA), -40.6 ± 78.8 and 1.25 ± 0.49 (EWMA-W), and -80.1 ± 69.0 and 1.57 ± 0.57 (EWMA-L) over the eight weeks. There were significant differences in performance between both successful and non-successful as well as top 5 and bottom 5 groups. In the last 6 weeks preceding competition, the successful and top five performance groups had a lower amount of training modifications due to injury and illness when compared to the non-successful (18%) and bottom five performance groups (22%). However, there were no significant differences and only small effect sizes for the differences in percentage of total training modified due to injury and illness. The three moving average methods for TSB and ACWR were all significantly different from one another (p<0.001, g=0.07-0.3).

Correlations between performance and the different acute and chronic internal TL variables are presented in Table 2. The correlations between performance and the percentage of training modified due to injury and illness were also small and non-significant. The correlations between the SMA and the two EWMA methods variables were very large (r=0.73-77, p<0.001). The correlation between the two EWMA methods for chronic – acute TL and ACWR were very large to nearly perfect (r=0.87 and 0.98 respectively, p<0.001).

TABLE 2 ABOUT HERE

Following the correlation analysis, the cohort was divided into successful and non-successful along with top five and bottom five performance groups. Acute, chronic, TSB and ACWR as SMA for successful and non-successful performance groups are presented in Figure 1A-C. These same variables for the top five and bottom five performance groups are displayed in Figure2A-C.

FIGURE1A-C ABOUT HERE
FIGURE 2A-C ABOUT HERE

The differences between higher and lower performing groups and top five and bottom five performance groups are presented in Table 3 and Table 4 respectively. Between the high and lower performing group, there was a significant difference between VOL21 TSB and ACWR variables as SMA. Between the top five and bottom five performance groups, there were also significant differences between CHANGE21 TSB and ACWR variables as SMA. The mean differences between successful and non-successful groups in TSB and ACWR as SMA are also shown in Cumming estimation plots (Figures 3A-B). There were no significant differences between groups when using the two EWMA methods.

TABLE 3 AND TABLE 4 ABOUT HERE
FIGURE 3A-B ABOUT HERE

DISCUSSION

Our first hypothesis was that there would be significant correlations between sRPE TL and performance in addition to significant differences in the same variables between higher and lower performers. Several sRPE TL variables were moderately correlated to performance and differentiated between higher and lower performers. These correlations were present even when analysing the data with different moving average methods. In particular, performance was significantly correlated with TSB and ACWR CHANGE21 as SMA (r=-0.49 and 0.43, p=0.02 and 0.05). Competitive performance was also significantly correlated with ACWR VOL21 in the two EWMA methods (r=-0.48 and -0.43 p=0.03 and 0.05; for interest SMA ACWR VOL21 r=-0.41 and p=0.07)). There were no significant differences between the moving average methods for correlations with performance when examined with r-z transformation. As such, a lower magnitude of change and volatility in the ACWR preceding competition seem to be moderately correlated to increased competitive performance.

Examining the differences between higher and lower performing groups, CHANGE21 and VOL21 TSB and the ACWR as SMA appeared to distinguish between higher and lower performing groups. The TSB and ACWR VOL21 as SMA were significantly lower in the successful group (p=0.03 and 0.03, g=0.32 and 1.07). Although these VOL21 differences were not significant when comparing the top five and bottom five performances (potentially due to sample size), there was a moderate effect size for both (g=0.91 and 1.16). Further, the TSB and ACWR CHANGE21 as SMA were significantly lower in the top five versus bottom five performances (p=0.04 and 0.05, g=1.43 and 1.33). It is notable that the two EWMA methods did not demonstrate any significant differences between groups. This is in opposition to our second hypothesis that TL variables calculated using EWMA would better separate higher and lower performing groups than a SMA.

There were no consistent relationships between performance and absolute TL variables on the day of competition. This raises the consideration that planning training around having an optimal level of internal TL at competition (e.g. TSB of 90 arbitrary units or an ACWR of 0.6) may not be as important as minimizing change and/or volatility of these measures in the competition taper. However, it should be mentioned that the subjects in this study were from the same national team who all trained together at the same set times with very similar training methods. Absolute values for TL measures may have a performance relationship when comparing groups that are not from the same team or do not train in a similar fashion. Based upon this, more research is warranted in different sports and different teams on the relationship between levels of TL variables on the day of competition and performance.

The comparison of the different moving average methods was designed to improve our understanding of the most suitable methods for TL calculation. There were significant differences between TSB and the ACWR calculated using the SMA, EWMA-W and EWMA-L. The very large correlations between SMA and both EWMA-W and EWMA-L (r=0.73-0.77) were greater than those presented in contemporary research on the topic[23]. The nearly perfect linear correlations and low magnitudes of effect between the two EWMA methods show that these methods may be interchangeable provided practitioners understand how to interpret any differences. Although all calculation methods showed some significant correlation with performance, the SMA was also the only method that demonstrated significant differences ($p<0.05$) between successful and non-successful groups. This finding is interesting when compared to previous research that determined the sensitivity of EWMA-W to likelihoods of injury was superior to SMA.[23] A potential explanation for this difference may be previous research examined likelihood of injury instead of performance and used external TL measures instead of internal TL measures in their analysis. This previous research also employed logistic regression models to create likelihoods of injury instead of comparing against actual injury incidents. There is very little research comparing EWMA to SMA and both have theoretical concerns. However, if applying the principle of parsimony (Occam's razor)[35] to help decide between moving average methods, SMA may be a superior alternative as it is a simpler for practitioners to apply. In this study, it appeared more sensitive to performance than the EWMA variations. However, further research is warranted in order to fully understand moving average methods impact on TL variables, their appropriateness in different sports and use with internal/external TL constructs. This would also include if other moving average methods (e.g. double exponential smoothing) may be more appropriate than those presented in this investigation.

Limitations of this investigation include the sole use of sRPE TL measures without any comparison with an external TL measure. As mentioned in the methods section, we were unable to use external TL measures (i.e. volume load, reps, sets, or intensity) due to the respective National Olympic Committee not consenting to record or release this data for any form of publication. Another potential limitation of this investigation was the requirement that subjects post a competition total (i.e. a successful lift in both snatch and clean & jerk) to be included in analysis. This excluded four subjects from the analysis that may have strengthened/weakened any results. These subjects were excluded from analysis due to methodological (i.e. calculating correlations with percentage of 12-month personal best competition total is skewed if only one lift is completed) and conceptual issues with determining in which group these athletes should be assigned due to potential confounding factors. Finally, due to the number of subjects, the specific context of this investigation and not having repeated measures of performance over time, practitioners should interpret this investigation's findings and level of evidence as a case study that may only be applicable for weightlifting athletes. More research is needed in other elite populations on the relationship between internal TL and performance.

PRACTICAL APPLICATIONS

Based on the outcomes of this study we suggest that a large amount of change or volatility in internal TL TSB or ACWR during the competition taper was detrimental to performance, at least when calculated using SMA. This suggests that large changes in internal TL TSB or ACWR should be avoided in the 21 days before competition. This would seem important for both technical coaches and other staff (e.g. strength & conditioning coaches) involved in training and taper planning before competition to consider. Practitioners may use different moving average methods to calculate internal TL however the SMA is a simpler method and appeared to better explain performance in this study. Lastly, the application of this data to other sports besides weightlifting requires further consideration.

CONCLUSIONS

The change and volatility of the TSB and ACWR in the taper were moderately correlated to performance and also differentiated between higher and lower performers in this cohort of elite weightlifters. The correlation results were present when analysing the data with all three different moving average methods. However, the simple moving average was the only training load calculation method that demonstrated a significant difference between higher and lower weightlifting performance. There were no consistent relationships between performance and the TSB or ACWR on the day of competition in this group of elite weightlifters; regardless of moving average method used. Although training load monitoring with sRPE can be applied to a number of sports, it remains to be seen whether there are similar relationships with performance in other sports. Further, in this investigation, calculating training load with a simple moving average seemed to better explain performance compared to the exponentially weighted moving averages.

ACKNOWLDGEMENTS

JC drafted the initial concept and all authors contributed to drafting, critical revision and approval of the final manuscript. Thank you to Aaron Coutts and Sophia Nimphius for advice and feedback on the theory and methods applied in this investigation. There was no additional financial or material support.

SUPPLEMENTAL FILE

A supplemental file is provided with the code in R for all of the statistical methods provided in this response.

REFERENCES

1. Cunanan AJ, DeWeese BH, Wagle JP, et al. The General Adaptation Syndrome: A foundation for the concept of periodization. *Sports Med.* 2018;48(4):787-797.
2. Bourdon PC, Cardinale M, Murray A, et al. Monitoring athlete training loads: Consensus statement. *Int J Sports Physiol Perform.* 2017;12(Suppl 2):161-170.
3. Banister EW, Calvert, T.W., Savage, M.V. and Bach, T.M. A Systems Model of Training for Athletic Performance. *Aust J Sci Med.* 1975(7):57-61.
4. Allen H, Coggan, A. *Training and Racing With A Powermeter.* 2nd ed. Boulder, CO: Velopress; 2010.
5. Hulin BT, Gabbett TJ, Blanch P, Chapman P, Bailey D, Orchard JW. Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *Br J Sports Med.* 2014;48(8):708-712.
6. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform.* 2019;14(2):270-273.
7. Coyne JOC, Gregory Haff G, Coutts AJ, Newton RU, Nimphius S. The Current State of Subjective Training Load Monitoring—a Practical Perspective and Call to Action. *Sports Med Open.* 2018;4(1):58.
8. Bompa TaH, G.G. *Periodization: Theory and methodology of training.* Fifth ed. Champaign, IL: Human Kinetics; 2009.
9. Scott BR, Duthie GM, Thornton HR, Dascombe BJ. Training monitoring for resistance exercise: Theory and applications. *Sports Med.* 2016;46(5):687-698.
10. Drew MK, Finch CF. The relationship between training load and injury, illness and soreness: A systematic and literature review. *Sports Med.* 2016;46(6):861-883.
11. McLaren SJ, Macpherson TW, Coutts AJ, Hurst C, Spears IR, Weston M. The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis. *Sports Med.* 2018;48(3):641-658.
12. Aughey RJ, Elias GP, Esmaeili A, Lazarus B, Stewart AM. Does the recent internal load and strain on players affect match outcome in elite Australian football? *J Sci Med Sport.* 2016;19(2):182-186.
13. Graham SR, Cormack S, Parfitt G, Eston R. Relationships between model predicted and actual match performance in professional Australian Footballers during an in-season training macrocycle. *Int J Sports Physiol Perform.* 2017:1-25.
14. Lazarus BH, Stewart AM, White KM, et al. Proposal of a Global Training Load Measure Predicting Match Performance in an Elite Team Sport. *Front Physiol.* 2017;8:930.
15. Wallace LK, Slattery KM, Coutts AJ. A comparison of methods for quantifying training load: relationships between modelled and actual training responses. *Eur J Appl Physiol.* 2014;114(1):11-20.
16. Wood RE, Hayter S, Rowbottom D, Stewart I. Applying a mathematical model to training adaptation in a distance runner. *Eur J Appl Physiol.* 2005;94(3):310-316.
17. Suzuki S, Sato T, Maeda A, Takahashi Y. Program design based on a mathematical model using rating of perceived exertion for an elite Japanese sprinter: a case study. *J Strength Cond Res.* 2006;20(1):36-42.
18. Foster C. Monitoring training in athletes with reference to overtraining syndrome. *Med Sci Sports Exerc.* 1998;30(7):1164-1168.

19. Putlur P, Foster C, Miskowski JA, et al. Alteration of immune function in women collegiate soccer players and college students. *Journal of Sports Science & Medicine.* 2004;3(4):234-243.
20. Black F, and Scholes, M. The pricing of options and corporate liabilities. *J Political Econ.* 1973;81(4):637-659.
21. Williams S, West S, Cross MJ, Stokes KA. Better way to determine the acute:chronic workload ratio? *Br J Sports Med.* 2016;51(3):209.
22. Menaspà P. Are rolling averages a good way to assess training load for injury prevention? *Br J Sports Med.* 2017;51(7):618-619.
23. Murray NB, Gabbett TJ, Townshend AD, Blanch P. Calculating acute:chronic workload ratios using exponentially weighted moving averages provides a more sensitive indicator of injury likelihood than rolling averages. *Br J Sports Med.* 2016;51(9):749.
24. Lolli L, Batterham AM, Hawkins R, et al. Mathematical coupling causes spurious correlation within the conventional acute-to-chronic workload ratio calculations. *Br J Sports Med.* 2017.
25. Windt J, Gabbett TJ. Is it all for naught? What does mathematical coupling mean for acute:chronic workload ratios? *Br J Sports Med.* 2018.
26. Coyne JOC, Nimphius S, Newton RU, Haff GG. Does mathematical coupling matter to the Acute to Chronic Workload Ratio? A case study from elite sport. *Int J Sports Physiol Perform.* 2019:1-8.
27. Raysmith BP, Drew MK. Performance success or failure is influenced by weeks lost to injury and illness in elite Australian Track and Field athletes: a 5-year prospective study. *J Sci Med Sport.* 2016;19(10):778-783.
28. Christen J, Foster C, Porcari JP, Mikat RP. Temporal robustness of the session rating of perceived exertion. *Int J Sports Physiol Perform.* 2016;11(8):1088-1093.
29. Foster C, Florhaug JA, Franklin J, et al. A new approach to monitoring exercise training. *J Strength Cond Res.* 2001;15(1):109-115.
30. Busso T, Hakkinen K, Pakarinen A, Kauhanen H, Komi PV, Lacour JR. Hormonal adaptations and modelled responses in elite weightlifters during 6 weeks of training. *Eur J Appl Physiol Occup Physiol.* 1992;64(4):381-386.
31. Bosquet L, Montpetit J, Arvisais D, Mujika I. Effects of tapering on performance: a meta-analysis. *Med Sci Sports Exerc.* 2007;39(8):1358-1365.
32. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise.* 2009;41(1):3-12.
33. Rosenthal R. Parametric measures of effect size. In: Cooper H, Hedges, L.V., ed. *The Handbook of Research Synthesis.* New York, NY: Sage; 1994.
34. Cumming G, Calin-Jageman R. *Introduction to the New Statistics: Estimation, Open Science, and Beyond.* Routledge; 2016.
35. Gauch HJC, H.J. Jr. *Scientific Method in Practice.* Cambridge Univeristy Press; 2003.

Table 1. Descriptive statistics of elite weightlifters' competition results and modified training due to injury and illness prior to a qualifying competition for the 2016 Olympic Games.

	n	*%12PB*	*p*	*g*	*%WR*	*p*	*g*	*%INJ*	*p*	*g*
OVERALL	21	99.1 ± 3.0			95.4 ± 3.5			34.8 ± 41.5		
S	10	101 ± 1.7			97.7 ± 2.8			28.1 ± 41.0		
NS	8	96.1 ± 1.7	0.00**	3.03	93.3 ± 3.2	0.01**	1.40	46.1 ± 48.9	0.47	0.24
TOP5	5	103 ± 1.5			99.5 ± 1.6			16.2 ± 20.6		
BOT5	5	95.1 ± 1.3	0.00**	4.93	93.2 ± 2.6	0.00**	2.61	38.1 ± 51.3	0.48	0.20

*Note: OVERALL – complete cohort, S – successful performance group, NS – non-successful performance group, TOP5 – top five performance group, BOT5 – bottom five performance group, n – number of subjects, %12PB – percentage of 12 month personal best total, %WR – percentage of world record total, %INJ – percentage of training affected by injury in last 6 weeks, g – Hedge's effect size, * - p>0.05, **p>0.01, p>0.001****

Table 2. Correlations between different internal training load variables and performance for elite weightlifters at a qualifying competition for the 2016 Olympic Games.

	SMA		EWMA-W			EWMA-L		
	r [95% CI]	*p*	*r [95% CI]*	*p*	*SMA R-z p*	*r [95% CI]*	*p*	*SMA R-z p*
ABSOLUTE								
Acute TL	0.18 [-0.27, 0.57]	0.43	0.11 [-0.33, 0.52]	0.63	0.83	0.11 [-0.34, 0.52]	0.64	0.83
Chronic TL	0.01 [-0.42, 0.44]	0.97	0.08 [-0.36, 0.49]	0.73	0.83	0.06 [-0.38, 0.48]	0.80	0.88
TSB	-0.27 [-0.63, 0.19]	0.24	-0.07 [-0.49, 0.37]	0.77	0.54	-0.12 [-0.53, 0.33]	0.59	0.64
ACWR	0.19 [-0.27, 0.57]	0.42	0.01 [-0.42, 0.44]	0.96	0.59	0.02 [-0.42, 0.44]	0.95	0.61
CHANGE21								
Acute TL	0.39 [-0.05, 0.70]	0.08	0.35 [-0.09, 0.68]	0.12	0.89	0.31 [-0.14, 0.65]	0.17	0.78
Chronic TL	-0.03 [-0.45, 0.41]	0.90	0.24 [-0.21, 0.61]	0.29	0.41	0.14 [-0.31, 0.54]	0.55	0.61
TSB	-0.49 [-0.76, 0.07]	0.02*	-0.36 [-0.68, 0.09]	0.11	0.63	-0.34 [-0.67, 0.11]	0.13	0.59
ACWR	0.43 [-0.01, 0.72]	0.05*	0.33 [-0.12, 0.67]	0.14	0.73	0.42 [-0.01, 0.72]	0.06	0.97
VOL21								
Acute TL	-0.28 [-0.63, 0.17]	0.22	-0.22 [-0.59, 0.24]	0.34	0.85	-0.17 [-0.56, 0.29]	0.47	0.73
Chronic TL	0.04 [-0.40, 0.47]	0.86	-0.05 [-0.48, 0.39]	0.81	0.79	0.28 [-0.17, 0.64]	0.21	0.46
TSB	-0.34 [-0.67, 0.10]	0.13	-0.30 [-0.65, 0.16]	0.19	0.89	-0.31 [-0.65, 0.14]	0.17	0.92
ACWR	-0.41 [-0.71, 0.03]	0.07	-0.48 [-0.75, -0.06]	0.03*	0.79	-0.43 [-0.73, 0.00]	0.05*	0.94

*Note: ABSOLUTE - the value on the day of the competition, CHANGE21 - the value 21 days prior to competition subtracted from the value on the day of the competition, VOL21 - the volatility (standard deviation) of values in the last 21 days prior to competition, TL – training load, TSB – training stress balance; ACWR – acute to chronic workload ratio, SMA – simple moving average, EWMA-W – exponentially weighted moving averages as per Williams et al [26], EWMA-L - exponentially weighted moving averages as per Lazarus et al [19], * - p>0.05*

Table 3. The differences in internal training load variables between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

	SMA					***EWMA-W***					***EWMA-L***				
	NS	***S***	***β%***	***p***	***g***	***NS***	***S***	***β%***	***p***	***g***	***NS***	***S***	***β%***	***p***	***g***
ABSOLUTE															
Acute TL	159 ± 101	156 ± 101	-1.5	0.84	0.12	153 ± 85.3	138 ± 85.7	-10.2	0.58	0.16	201 ± 86.8	186 ± 93.9	-7.3	0.74	0.16
Chronic TL	272 ± 108	255 ± 107	-6.4	0.74	0.15	235 ± 89.1	221 ± 91.3	-6.0	0.74	0.15	246 ± 88.3	237 ± 77.3	-3.6	0.82	0.10
TSB	113 ± 90.7	98.6 ± 45.5	-14.4	0.63	0.24	81.8 ± 44.5	83.4 ± 30.7	-2.0	0.64	0.04	45.3 ± 48.5	51.1 ± 37.1	12.5	0.78	0.13
ACWR	0.60 ± 0.25	0.57 ± 0.16	-4.1	0.80	0.12	0.64 ± 0.15	0.59 ± 0.12	-7.8	0.46	0.34	0.82 ± 0.15	0.75 ± 0.15	-7.8	0.40	0.39
CHANGE21															
Acute TL	-223 ± 181	-170 ± 107	-26.1	0.45	0.35	-254 ± 183	-187 ± 125	-30.5	0.36	0.42	-178 ± 126	-144 ± 103	-20.8	0.54	0.28
Chronic TL	-74.2 ± 59.0	-99.7 ± 83.1	28.4	0.48	0.33	-106 ± 83.3	-94.3 ± 85.6	-11.8	0.77	0.13	-14.4 ± 42.0	-17.5 ± 60.5	21.5	0.91	0.05
TSB	149 ± 155	70.3 ± 77.1	-69.3	0.18	0.63	148 ± 114	92.2 ± 67.1	-46.1	0.21	0.59	163 ± 101	126 ± 58.7	--24.8	0.34	0.44
ACWR	-0.46 ± 0.44	-0.36 ± 0.25	-24.0	0.56	0.27	-0.50 ± 0.12	-0.44 ± 0.09	-13.2	0.60	0.24	-0.62 ± 0.22	-0.55 ± 0.18	-12.5	0.47	0.34
VOL21															
Acute TL	93.5 ± 65.1	74.5 ± 33.0	-22.4	0.93	0.04	94.9 ± 59.7	82.1 ± 31.3	-14.4	0.94	0.01	65.1 ± 44.4	60.8 ± 23.8	-0.07	0.71	0.26
Chronic TL	35.1 ± 18.2	39.2 ± 23.4	11.0	0.69	0.18	42.6 ± 28.2	43.8 ± 17.9	-3.0	0.91	0.05	20.0 ± 11.0	23.9 ± 10.2	18.1	0.44	0.36
TSB	80.0 ± 53.5	44.4 ± 27.4	-56.6	0.03*	1.15	57.1 ± 33.6	42.3 ± 21.0	-29.3	0.27	0.52	53.3 ± 36.3	44.2 ± 18.0	-18.8	0.94	0.16
ACWR	0.25 ± 0.10	0.16 ± 0.06	-46.2	0.03*	1.07	0.19 ± 0.05	0.16 ± 0.03	-0.15	0.16	0.72	0.19 ± 0.07	0.17 ± 0.05	-8.9	0.59	0.25

Note: ABSOLUTE - the value on the day of the competition, CHANGE21 - the value 21 days prior to competition subtracted from the value on the day of the competition, VOL21 - the volatility (standard deviation) of values in the last 21 days prior to competition, TL – training load, TSB – training stress balance; ACWR – acute to chronic workload ratio, SMA – simple moving average, EWMA-W – exponentially weighted moving averages as per Williams et al [26], EWMA-L - exponentially weighted moving averages as per Lazarus *et al* [19]*, S – successful performance group, NS – non-successful performance group, β% - beta percentage difference, p – p-value, g – Hedge's effect size, * - p>0.05*

Table 4. The differences in internal training load variables between the top 5 and bottom 5 performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

	SMA					***EWMA-W***					***EWMA-L***				
	BOT5	***TOP5***	***β%***	***p***	***g***	***BOT5***	***TOP5***	***β%***	***p***	***g***	***BOT5***	***TOP5***	***β%***	***p***	***g***
ABSOLUTE															
Acute TL	184 ± 117	191 ± 131	4.1	0.93	0.05	178 ± 98.0	164 ± 116	-9.0	0.84	0.11	224 ± 97.9	212 ± 123	-5.6	0.88	0.09
Chronic TL	294 ± 109	265 ± 125	-10.5	0.71	0.22	256 ± 95.7	242 ± 116	-5.8	0.84	0.12	261 ± 89.0	249 ± 92.1	-4.4	0.85	0.11
TSB	109 ± 91.3	74.1 ± 19.0	-34.5	0.44	0.42	78.1 ± 41.3	78.0 ± 28.7	-0.0	1.00	0.00	36.9 ± 48.0	37.3 ± 47.1	0.7	0.99	0.01
ACWR	0.62 ± 0.25	0.66 ± 0.17	-6.9	0.77	0.17	0.67 ± 0.15	0.62 ± 0.17	-7.9	0.64	0.27	0.85 ± 0.16	0.81 ± 0.21	-5.3	0.73	0.20
CHANGE21															
Acute TL	-277 ± 185	-123 ± 135	-76.0	0.17	0.85	-304 ± 192	-161 ± 154	-64.6	0.23	0.74	-203 ± 136	-118 ± 135	-52.4	0.35	0.56
Chronic TL	-67.8 ± 57.3	-93.0 ± 113	28.1	0.67	0.26	-113 ± 89.1	-71.7 ± 117.5	-40.5	0.55	0.35	-6.5 ± 41.9	-1.9 ± 85.5	-32.4	0.92	0.06
TSB	210 ± 147	30.1 ± 61.2	-158.8	0.04*	1.43	192 ± 113	88.8 ± 71.5	-84.5	0.12	0.97	196 ± 104	116 ± 64.8	-54.3	0.18	0.83
ACWR	-0.65 ± 0.26	-0.24 ± 0.28	-99.9	0.05*	1.33	-0.60 ± 0.16	-0.41 ± 0.25	41.1	0.28	0.35	-0.74 ± 0.18	-0.52 ± 0.22	-37.4	0.20	0.95
VOL21															
Acute TL	110 ± 74.0	65.1 ± 20.6	-53.6	0.25	0.66	109 ± 65.1	76.4 ± 19.7	-37.2	0.33	0.55	75.7 ± 48.0	56.4 ± 19.4	-31.0	0.43	0.47
Chronic TL	34.5 ± 16.0	38.1 ± 30.1	9.6	0.82	0.13	48.4 ± 29.5	42.2 ± 19.1	-14.7	0.70	0.22	22.4 ± 10.2	28.1 ± 12.1	26.4	0.44	0.46
TSB	91.6 ± 66.9	40.7 ± 23.6	-81.0	0.15	0.91	66.2 ± 38.6	39.7 ± 16.6	-52.6	0.20	0.80	64.3 ± 39.5	39.0 ± 9.4	-51.7	0.23	0.69
ACWR	0.24 ± 0.09	0.14 ± 0.06	-50.1	0.08	1.16	0.19 ± 0.06	0.15 ± 0.02	-25.8	0.19	0.95	0.22 ± 0.06	0.16 ± 0.04	-38.0	0.12	1.35

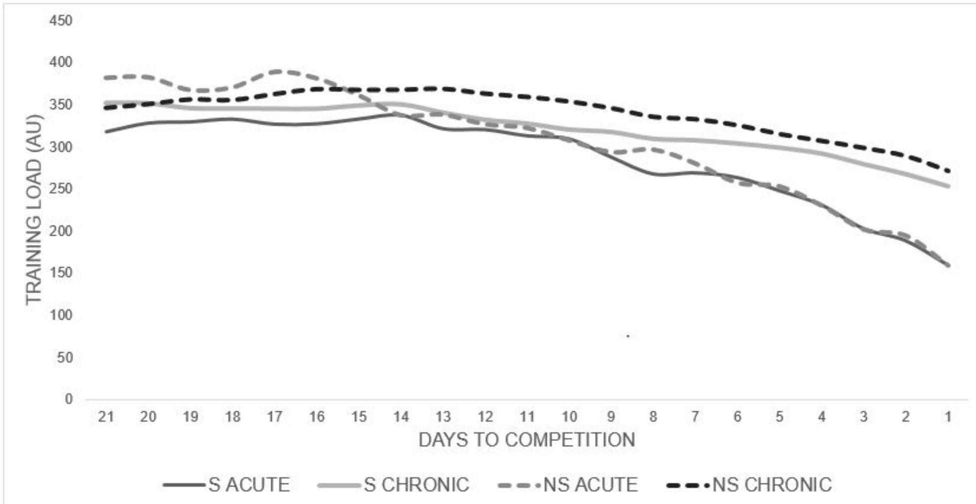
Note: ABSOLUTE - the value on the day of the competition, CHANGE21 - the value 21 days prior to competition subtracted from the value on the day of the competition, VOL21 - the volatility (standard deviation) of values in the last 21 days prior to competition, TL – training load, TSB – training stress balance; ACWR – acute to chronic workload ratio, SMA – simple moving average, EWMA-W – exponentially weighted moving averages as per Williams et al [26], EWMA-L - exponentially weighted moving averages as per Lazarus *et al* [19]*, S – successful performance group, NS – non-successful performance group, β% - beta percentage difference, p – p-value, g – Hedge's effect size, * - p>0.05*

FIGURE CAPTIONS

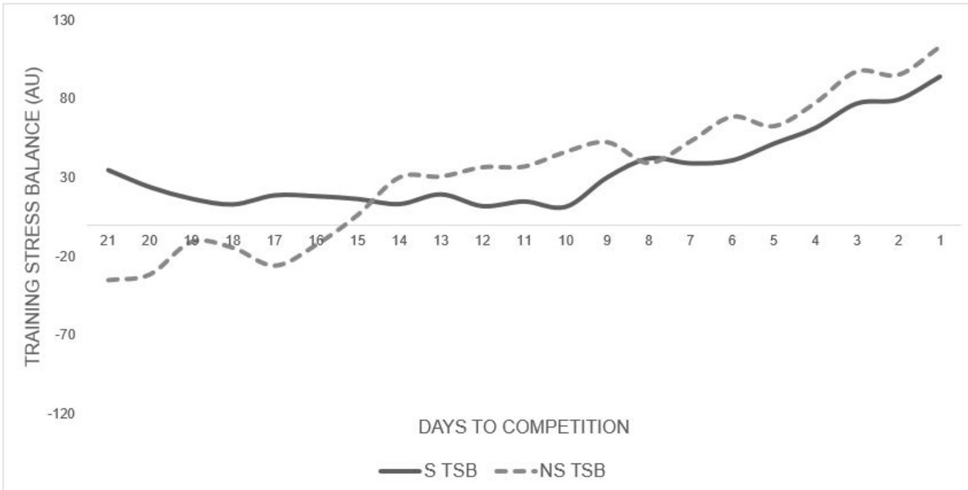
Figure 1A-C. A comparison of internal training load variables between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.
NOTES: NS – non-successful group, S – successful group, AU – arbitrary units, TSB – training stress balance, ACWR – acute to chronic workload ratio

Figure 2A-C. A comparison of internal training load variables between the top five and bottom five performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.
NOTES: NS – non-successful group, S – successful group, AU – arbitrary units, TSB – training stress balance, ACWR – acute to chronic workload ratio

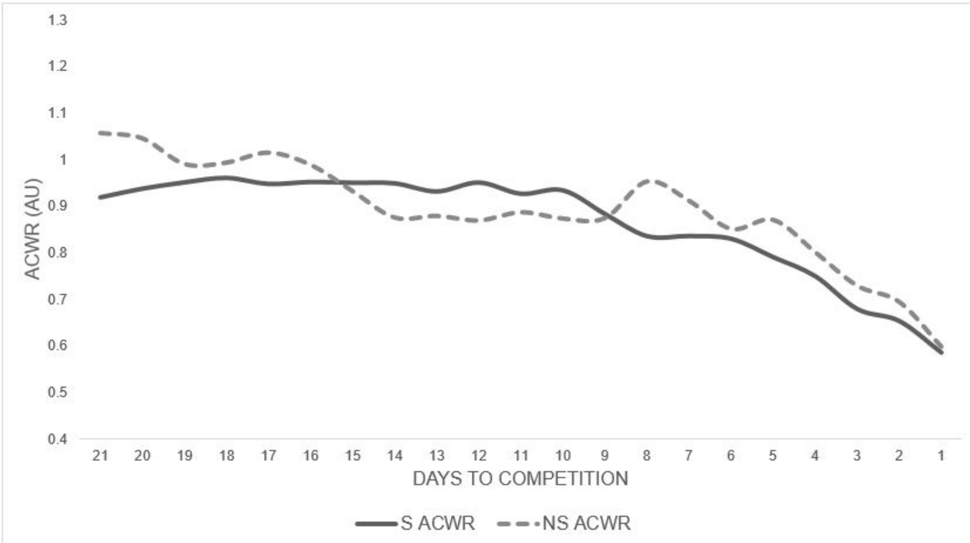
Figure 3A-B. Cumming estimation plots of (A) Training stress balance and (B) Acute to chronic workload ratio differences as simple moving averages between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.
NOTES: NS – non-successful group, S – successful group, ABSOLUTE - the value on the day of the competition, CHANGE21 - the value 21 days prior to competition subtracted from the value on the day of the competition, VOL21 - the volatility (standard deviation) of values in the last 21 days prior to competition, TSB – training stress balance, ACWR – acute to chronic workload ratio, AU – arbitrary units



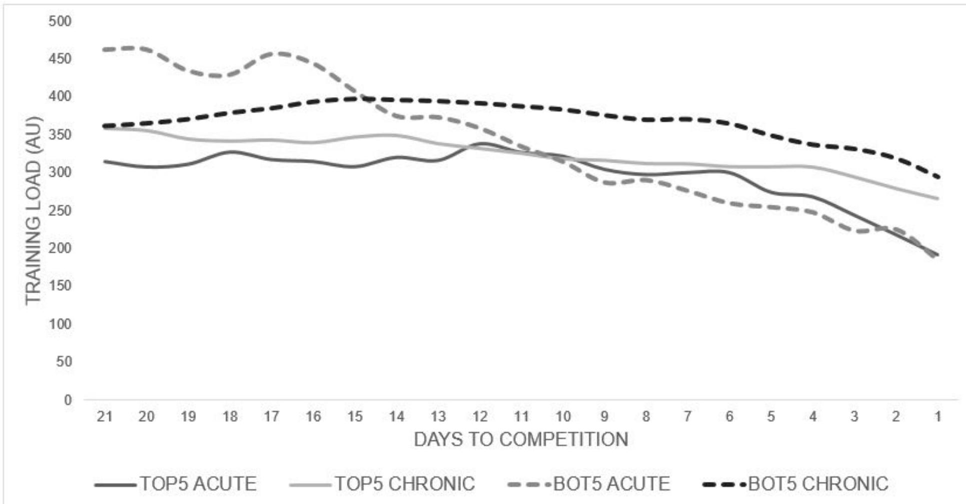
224x118mm (96 x 96 DPI)



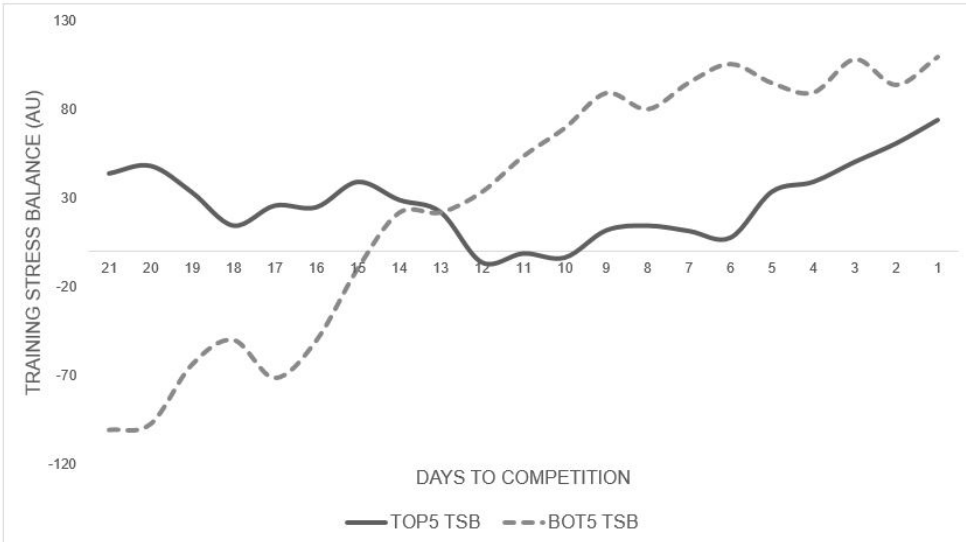
230x118mm (96 x 96 DPI)



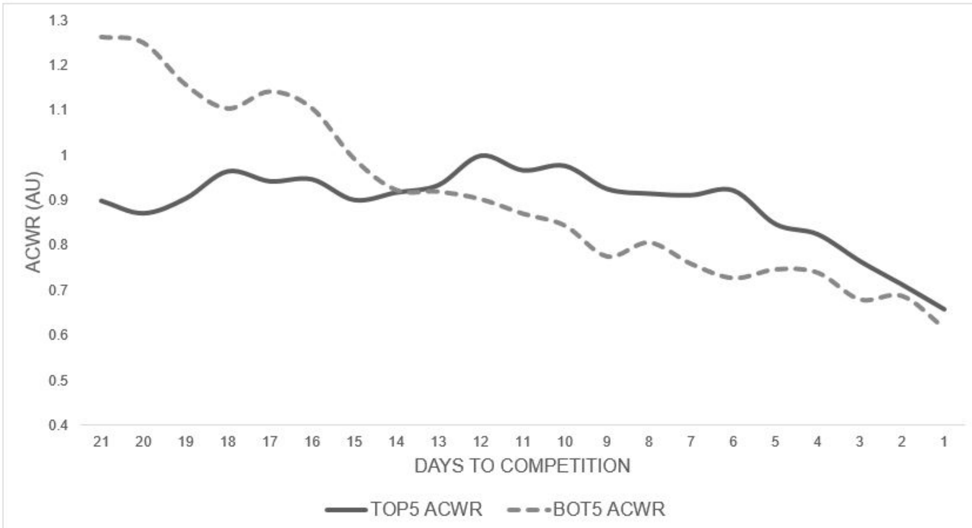
225x128mm (96 x 96 DPI)



226x120mm (96 x 96 DPI)



226x127mm (96 x 96 DPI)



224x123mm (96 x 96 DPI)

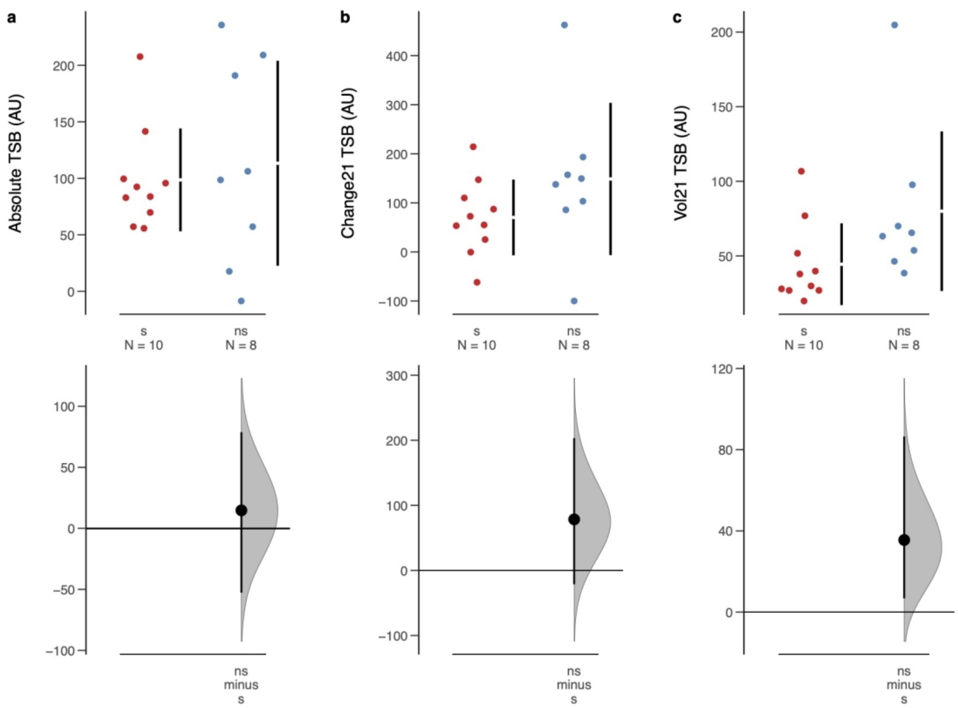


Figure 3A.

296x209mm (150 x 150 DPI)

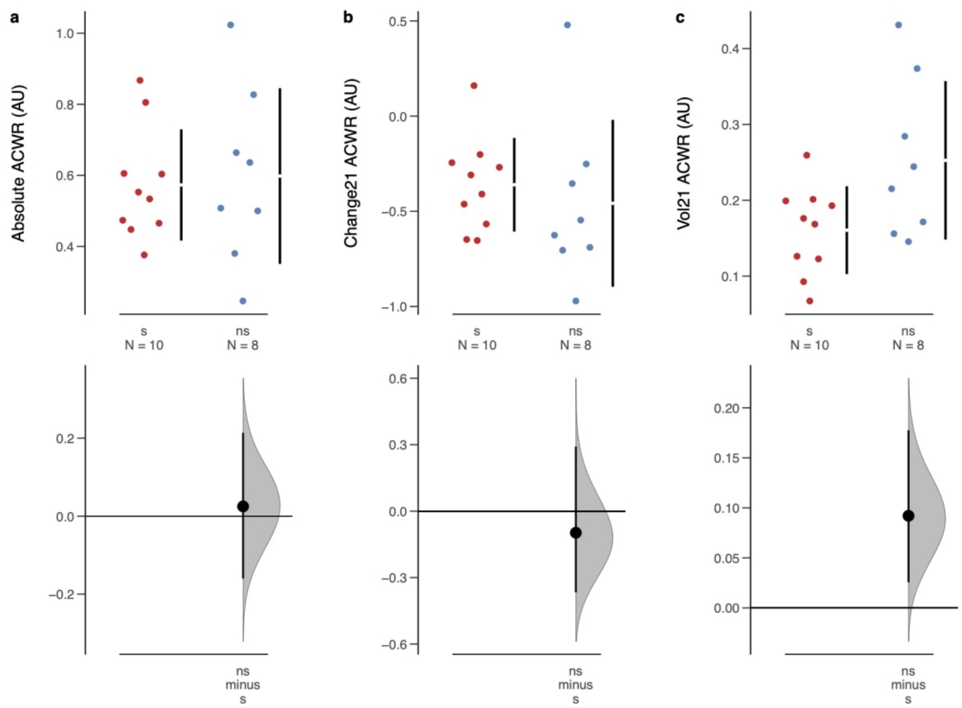


Figure 3B.

296x209mm (150 x 150 DPI)

```
#load required packages
library(tidyverse)
library(dplyr)
library(ggplot2)
library(cocor)
library(corrplot)
library(corrr)
library(car)
library(dabestr)
library(GGally)
library(Hmisc)
library(readxl)
library(cowplot)
library(pwr)
library(ggpubr)
library(psych)
library(lattice)
library(mbir)

#import data
wl_desc <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "desc")
wl_tl21 <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "tl21")
wl_compl <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "tl")
View(wl_desc)
View(wl_tl21)
View(wl_compl)

######### PREPARE DATA ############

#get data for overall  stats
#apply multi.sapply function for descriptive stats
multi.sapply <- function(...) {
  arglist <- match.call(expand.dots = FALSE)$...
  var.names <- sapply(arglist, deparse)
  has.name <- (names(arglist) != "")
  var.names[has.name] <- names(arglist)[has.name]
  arglist <- lapply(arglist, eval.parent, n = 2)
  x <- arglist[[1]]
  arglist[[1]] <- NULL
  result <- sapply(arglist, function (FUN, x) sapply(x, FUN, na.rm=T), x)
  colnames(result) <- var.names[-1]
  return(result)
}
```

```
#get mean/sd for overall cohort
overall_wl <- multi.sapply(wl_compl[,2:13], mean, sd)
overall_wl

#get correlations between moving average methods
movAv_corData <- wl_compl[c(4:5, 8:9, 12:13)]
movAv_cor <- corr.test(movAv_corData, alpha=0.05, ci=T)
print(movAv_cor, short=F)

#get data for group stats
#include change function
change <- function(x){
  last(x)-first(x)}

wl_data1 <- wl_tl21 %>%
  group_by(id) %>%
  summarise(abs_raA = last(raA),
            abs_raC = last(raC),
            abs_raCA = last(raCA),
            abs_raACWR = last(raACWR),
            change_raA = change(raA),
            change_raC = change(raC),
            change_raCA = change(raCA),
            change_raACWR = change(raACWR),
            vol_raA = sd(raA),
            vol_raC = sd(raC),
            vol_raCA = sd(raCA),
            vol_raACWR = sd(raACWR))

wl_data2 <- wl_tl21 %>%
  group_by(id) %>%
  summarise(abs_ewma1A = last(ewma1A),
            abs_ewma1C = last(ewma1C),
            abs_ewma1CA = last(ewma1CA),
            abs_ewma1ACWR = last(ewma1ACWR),
            change_ewma1A = change(ewma1A),
            change_ewma1C = change(ewma1C),
            change_ewma1CA = change(ewma1CA),
            change_ewma1ACWR = change(ewma1ACWR),
            vol_ewma1A = sd(ewma1A),
            vol_ewma1C = sd(ewma1C),
            vol_ewma1CA = sd(ewma1CA),
            vol_ewma1ACWR = sd(ewma1ACWR),
            abs_ewma2A = last(ewma2A),
            abs_ewma2C = last(ewma2C),
```

```
            abs_ewma2CA = last(ewma2CA),
            abs_ewma2ACWR = last(ewma2ACWR),
            change_ewma2A = change(ewma2A),
            change_ewma2C = change(ewma2C),
            change_ewma2CA = change(ewma2CA),
            change_ewma2ACWR = change(ewma2ACWR),
            vol_ewma2A = sd(ewma2A),
            vol_ewma2C = sd(ewma2C),
            vol_ewma2CA = sd(ewma2CA),
            vol_ewma2ACWR = sd(ewma2ACWR),
            abs_strain = last(strain),
            abs_mono = last(mono),
            change_strain = change(strain),
            change_mono = change(mono),
            mean_strain = mean(strain),
            mean_mono = mean(mono))

wl_data <- left_join(wl_data1, wl_data2, by="id")
wl_data <- left_join(wl_data, wl_desc, by="id")
wl_data <- wl_data[,1:49]

wl_data <- wl_data %>%
  mutate(beta_abs_raA = abs_raA/mean(abs_raA),
         beta_abs_raC = abs_raC/mean(abs_raC),
         beta_abs_raCA = abs_raCA/mean(abs_raCA),
         beta_abs_raACWR = abs_raACWR/mean(abs_raACWR),
         beta_change_raA = change_raA/mean(change_raA),
         beta_change_raC = change_raC/mean(change_raC),
         beta_change_raCA = change_raCA/mean(change_raCA),
         beta_change_raACWR = change_raACWR/mean(change_raACWR),
         beta_vol_raA = vol_raA/mean(vol_raA),
         beta_vol_raC = vol_raC/mean(vol_raC),
         beta_vol_raCA = vol_raCA/mean(vol_raCA),
         beta_vol_raACWR = vol_raACWR/mean(vol_raACWR),
         beta_abs_ewma1A = abs_ewma1A/mean(abs_ewma1A),
         beta_abs_ewma1C = abs_ewma1C/mean(abs_ewma1C),
         beta_abs_ewma1CA = abs_ewma1CA/mean(abs_ewma1CA),
         beta_abs_ewma1ACWR = abs_ewma1ACWR/mean(abs_ewma1ACWR),
         beta_change_ewma1A = change_ewma1A/mean(change_ewma1A),
         beta_change_ewma1C = change_ewma1C/mean(change_ewma1C),
         beta_change_ewma1CA = change_ewma1CA/mean(change_ewma1CA),
         beta_change_ewma1ACWR = change_ewma1ACWR/mean(change_ewma1ACWR),
         beta_vol_ewma1A = vol_ewma1A/mean(vol_ewma1A),
         beta_vol_ewma1C = vol_ewma1C/mean(vol_ewma1C),
         beta_vol_ewma1CA = vol_ewma1CA/mean(vol_ewma1CA),
         beta_vol_ewma1ACWR = vol_ewma1ACWR/mean(vol_ewma1ACWR),
```

```
        beta_abs_ewma2A = abs_ewma2A/mean(abs_ewma2A),
        beta_abs_ewma2C = abs_ewma2C/mean(abs_ewma2C),
        beta_abs_ewma2CA = abs_ewma2CA/mean(abs_ewma2CA),
        beta_abs_ewma2ACWR = abs_ewma2ACWR/mean(abs_ewma2ACWR),
        beta_change_ewma2A = change_ewma2A/mean(change_ewma2A),
        beta_change_ewma2C = change_ewma2C/mean(change_ewma2C),
        beta_change_ewma2CA = change_ewma2CA/mean(change_ewma2CA),
        beta_change_ewma2ACWR = change_ewma2ACWR/mean(change_ewma2ACWR),
        beta_vol_ewma2A = vol_ewma2A/mean(vol_ewma2A),
        beta_vol_ewma2C = vol_ewma2C/mean(vol_ewma2C),
        beta_vol_ewma2CA = vol_ewma2CA/mean(vol_ewma2CA),
        beta_vol_ewma2ACWR = vol_ewma2ACWR/mean(vol_ewma2ACWR))

######## CORRELATIONS WITH PERFORMANCE ############
#scatterplot of pb v CA and ACWR abs, change21 and vol21 rolling averages with linear
regression lines
pb_CA_plot <- ggplot(wl_data, aes(x = abs_raCA, y = pb)) + geom_point(position="jitter",
alpha=0.8) + geom_smooth(method = "lm", se =F) + theme(legend.position = "bottom") +
labs(x="SMA Chronic - Acute", y="%12PB")
pb_ACWR_plot <- ggplot(wl_data, aes(x = abs_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR", y="%12PB")
pb_changeCA_plot <- ggplot(wl_data, aes(x = change_raCA, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA Chronic - Acute Change", y="%12PB")
pb_changeACWR_plot <- ggplot(wl_data, aes(x = change_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR Change", y="%12PB")
pb_volCA_plot <- ggplot(wl_data, aes(x = vol_raCA, y = pb)) + geom_point(position="jitter",
alpha=0.8) + geom_smooth(method = "lm", se =F) + theme(legend.position = "bottom") +
labs(x="SMA Chronic - Acute Volatility", y="%12PB")
pb_volACWR_plot <- ggplot(wl_data, aes(x = vol_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR Volatility", y="%12PB")
plot_grid(pb_CA_plot, pb_ACWR_plot, pb_changeCA_plot, pb_changeACWR_plot,
pb_volCA_plot, pb_volACWR_plot, align = "v", labels = "auto", ncol = 2)

#get rolling average correl data
wlRa_corData <- wl_data[c(2:13, 46)]
wlRa_cor <- corr.test(wlRa_corData, alpha=0.05, ci=T)
print(wlRa_cor, short=F)

#get ewma1 correl data
wlEwma1_corData <- wl_data[c(14:25, 46)]
wlEwma1_cor <- corr.test(wlEwma1_corData, alpha=0.05, ci=T)
print(wlEwma1_cor, short=F)
```

```
#get ewma2 correl data
wlEwma2_corData <- wl_data[c(26:37, 46)]
wlEwma2_cor <- corr.test(wlEwma2_corData, alpha=0.05, ci=T)
print(wlEwma2_cor, short=F)

#compare correlations in rolling average v ewma 1 (refer back to correlation data)
absA_compare <- cocor.indep.groups(0.18, 0.11, 21, 21, alternative = "two sided")
absC_compare <- cocor.indep.groups(0.01, 0.08, 21, 21, alternative = "two sided")
absCA_compare <- cocor.indep.groups(-0.27, -0.07, 21, 21, alternative = "two sided")
absACWR_compare <- cocor.indep.groups(0.19, 0.01, 21, 21, alternative = "two sided")
changeA_compare <- cocor.indep.groups(0.39, 0.35, 21, 21, alternative = "two sided")
changeC_compare <- cocor.indep.groups(-0.03, 0.24, 21, 21, alternative = "two sided")
changeCA_compare <- cocor.indep.groups(-0.49, -0.36, 21, 21, alternative = "two sided")
changeACWR_compare <- cocor.indep.groups(0.43, 0.33, 21, 21, alternative = "two sided")
volA_compare <- cocor.indep.groups(-0.28, -0.22, 21, 21, alternative = "two sided")
volC_compare <- cocor.indep.groups(0.04, -0.05, 21, 21, alternative = "two sided")
volCA_compare <- cocor.indep.groups(-0.34, -0.30, 21, 21, alternative = "two sided")
volACWR_compare <- cocor.indep.groups(-0.41, -0.48, 21, 21, alternative = "two sided")

#call results
absA_compare
absC_compare
absCA_compare
absACWR_compare
changeA_compare
changeC_compare
changeCA_compare
changeACWR_compare
volA_compare
volC_compare
volCA_compare
volACWR_compare

#compare correlations in rolling average v ewma 2 (refer back to correlation data)
absA_compare1 <- cocor.indep.groups(0.18, 0.11, 21, 21, alternative = "two sided")
absC_compare1 <- cocor.indep.groups(0.01, 0.06, 21, 21, alternative = "two sided")
absCA_compare1 <- cocor.indep.groups(-0.27, -0.12, 21, 21, alternative = "two sided")
absACWR_compare1 <- cocor.indep.groups(0.19, 0.02, 21, 21, alternative = "two sided")
changeA_compare1 <- cocor.indep.groups(0.39, 0.31, 21, 21, alternative = "two sided")
changeC_compare1 <- cocor.indep.groups(-0.03, 0.14, 21, 21, alternative = "two sided")
changeCA_compare1 <- cocor.indep.groups(-0.49, -0.34, 21, 21, alternative = "two sided")
changeACWR_compare1 <- cocor.indep.groups(0.43, 0.42, 21, 21, alternative = "two sided")
volA_compare1 <- cocor.indep.groups(-0.28, -0.17, 21, 21, alternative = "two sided")
volC_compare1 <- cocor.indep.groups(0.04, 0.28, 21, 21, alternative = "two sided")
volCA_compare1 <- cocor.indep.groups(-0.34, -0.31, 21, 21, alternative = "two sided")
```

```
volACWR_compare1 <- cocor.indep.groups(-0.41, -0.43, 21, 21, alternative = "two sided")

#call results
absA_compare1
absC_compare1
absCA_compare1
absACWR_compare1
changeA_compare1
changeC_compare1
changeCA_compare1
changeACWR_compare1
volA_compare1
volC_compare1
volCA_compare1
volACWR_compare1

######### DIFFERENCES BETWEEN HIGH AND LOWER PERFORMERS ########
#seperate groups
wlS <- wl_data %>%
  subset(group1 == "s")

wlNs <- wl_data %>%
  subset(group1 == "ns")

wlSNs <- bind_rows(wlNs, wlS)

wltop5 <- wl_data %>%
  subset(group2 == "top5")

wlbot5 <- wl_data %>%
  subset(group2 == "bot5")

wl5 <- bind_rows(wlbot5, wltop5)

#get mean/sd for overall cohort in last 21 days
wl_desc <- multi.sapply(wl_data[,46:49], mean, sd)
wl_desc

#get mean/sd for descriptive stats for S and Ns groups
wlS_desc <- multi.sapply(wlS[,2:49], mean, sd)
wlNs_desc <- multi.sapply(wlNs[,2:49], mean, sd)
wlS_desc
wlNs_desc

#get mean/sd for descriptive stats for top5 and bot5 groups
wltop5_desc <- multi.sapply(wltop5[,2:49], mean, sd)
```

```
wlbot5_desc <- multi.sapply(wlbot5[,2:49], mean, sd)
wltop5_desc
wlbot5_desc

#get beta differences between groups
wlSbeta_desc <- sapply(wlS[50:85], mean)
wlNsbeta_desc <- sapply(wlNs[50:85], mean)
wlSbeta_desc - wlNsbeta_desc

wltop5beta_desc <- sapply(wltop5[50:85], mean)
wlbot5beta_desc <- sapply(wlbot5[50:85], mean)
wltop5beta_desc - wlbot5beta_desc

#get standardised mean diffs for SNs rolling average data (including normality, variance and
mbi)
mbi_raSNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(2:13)], wlNs[,c(2:13)])

#standardised mean diff for SNs ewma1 data (including normality, variance and mbi)
mbi_ewma1SNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(14:25)], wlNs[,c(14:25)])

#standardised mean diff for SNs ewma2 data (including normality, variance and mbi)
mbi_ewma2SNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(26:37)], wlNs[,c(26:37)])

#magnitude based inferences for other data (including normality, variance and mbi)
mbi_otherSNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(46:48)], wlNs[,c(46:48)])

#convert SNs r to g (refer to results)
abs_raA_esSNs <- es_convert(-0.06, from="r", to="d")
abs_raCA_esSNs <- es_convert(0.12, from="r", to="d")
vol_raA_esSNs <- es_convert(0.02, from="r", to="d")
vol_raCA_esSNs <- es_convert(-0.5, from="r", to="d")
abs_ewma1A_esSNs <- es_convert(-0.08, from="r", to="d")
abs_ewma1CA_esSNs <- es_convert(0.02, from="r", to="d")
vol_ewma1A_esSNs <- es_convert(0, from="r", to="d")
vol_ewma1ACWR_esSNs <- es_convert(-0.34, from="r", to="d")
vol_ewma2A_esSNs <- es_convert(0.13, from="r", to="d")
vol_ewma2CA_esSNs <- es_convert(-0.08, from="r", to="d")
inj_esSNs <- es_convert(-0.12, from="r", to="d")

#standardised mean diff for top/bot5 rolling average data (including normality, variance and
mbi)
```

```
mbi_ra5 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(2:13)], wlbot5[,c(2:13)])

#standardised mean diff for top/bot5 ewma1 data (including normality, variance and mbi)
mbi_ewma15 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(14:25)], wlbot5[,c(14:25)])

#standardised mean diff for top/bot5 ewma2 data (including normality, variance and mbi)
mbi_ewma25 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(26:37)], wlbot5[,c(26:37)])

#standardised mean diff for top/bot5 other data (including normality, variance and mbi)
mbi_other5 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(46:48)], wlbot5[,c(46:48)])

#convert top/bot5 r to g
change_ewma1ACWR_es5 <- es_convert(-0.17, from="r", to="d")
vol_ewma1ACWR_es <- es_convert(-0.43, from="r", to="d")
change_ewma2ACWR_es5 <- es_convert(-0.43, from="r", to="d")
vol_ewma2ACWR_es5 <- es_convert(-0.56, from="r", to="d")

#convert other factors r to g
inj42SNs_es <- es_convert(-0.12, from="r", to="d")
inj425_es <- es_convert(-0.1, from="r", to="d")

#Cumming estimation plots for differences in rolling average ACWR
absACWR_est <- dabest(wlSNs, group1, abs_raACWR, idx=c("s", "ns"))
changeACWR_est <- dabest(wlSNs, group1, change_raACWR, idx=c("s","ns"))
volACWR_est <- dabest(wlSNs, group1, vol_raACWR, idx=c("s", "ns"))

absACWR_est_plot <- plot(absACWR_est, rawplot.ylabel = "Absolute ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
changeACWR_est_plot <- plot(changeACWR_est, rawplot.ylabel = "Change21 ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
volACWR_est_plot <- plot(volACWR_est, rawplot.ylabel = "Vol21 ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
plot_grid(absACWR_est_plot, changeACWR_est_plot, volACWR_est_plot, nrow=1, labels =
"auto")
```