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Compositional Analysis of Time- and Work-Based Intensity Distributions in Elite Cyclists During Training and Stage Racing

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Abstract

Cycling coaches frequently use training zones and zone distributions based around time in zone (TIZ) to analyse training data and to understand race demands. This study compared the intensity distribution of highly trained cyclists during training and racing using a novel work-in-zone (WIZ) method alongside the traditional TIZ approach. Twelve cyclists recorded their power output during 25 weeks of training and a 7-day stage race. Intensity zones were defined using a three-zone peak-power model, and intensity distribution (TIZ or WIZ) was analysed with compositional data analysis. There were significant main effects for context (training vs. racing) and zone type (TIZ vs. WIZ) on the ILR coordinates. ILR-1, which reflects the balance between Z1 and higher-intensity zones, was higher in training than racing and in TIZ compared with WIZ ($p < 0.0001$), indicating a relatively greater proportion of Z1 in these conditions. ILR-2, representing the balance within the higher-intensity zones, was significantly lower during racing and higher in TIZ compared with WIZ ($p < 0.0001$). These findings indicate the cyclists' training distribution differed substantially from the demands of racing, and that TIZ and WIZ can provide meaningfully different interpretations of intensity distribution. Where TIZ reflects only the time distribution spent within each zone, WIZ incorporates the weighting of intensity. This leads to particularly different results in racing, where intensity is more stochastic and characterised by greater extremes. Combining both methods may enhance understanding of training intensity distribution, race demands, and the difference between these contexts in endurance cyclists. Consequently, WIZ should be used in a complementary manner rather than as a replacement for TIZ.

Keywords: training zones; endurance cycling; intensity distribution; training load; cycling workload

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1. Introduction

Endurance athletes typically complete large training volumes distributed across a range of intensities, commonly referred to as zones, to prepare themselves for the demands of competition [1–3]. The distribution of training across these zones is inherently compositional, and the optimal balance is a topic of considerable debate [4,5]. As the proportions of time spent in each zone are interdependent, an increase in one necessarily reduces the others, and traditional analytical approaches can obscure the relative trade-offs between zones. In contrast, the compositional data analysis framework provides a mathematically

coherent way to examine these proportional relationships [6,7]. Despite the ongoing debate, it is agreed that a large proportion of training below the first lactate or ventilatory threshold is important for endurance performance [8,9], even though such training is not representative of competition demands [3,10].

Training intensity is typically divided into zones defined by physiological markers such as lactate or ventilatory thresholds [3,5,8]. These zones are then linked to corresponding measures of heart rate, pace, or power output, depending on the sport [11,12]. Alternatively, zones can be defined using percentage of maximum heart rate, power bands, percentage of a defined threshold level [13,14], or by estimating physiological breakpoints from a mean-max power curve [15,16]. The quantification of training within these zones is most commonly expressed as 'time in zone' (TIZ) but can also be quantified according to session rate of perceived exertion (sRPE) or session goal [17–19]. There is, however, some disparity between these methods. Athletes often perceive their training as more intense than TIZ measures indicate, with sRPE consistently reflecting higher intensities than zones defined by heart rate or power. This discrepancy is likely due to differences in workout structure (e.g., stochastic vs. steady efforts) and the influence of total session volume. For example, a continuous 30 min effort and thirty 1 min intervals performed at the same power output may yield the same average power and kJ of work completed, but very different heart rate and sRPE TIZ distributions [12,18,19], despite having identical external TIZ values. These differences become even more pronounced when athletes are fatigued, as maximum and average heart rate and/or power output often decrease while sRPE increases [20]. Additional factors such as hydration status and general physiological maintenance also contribute to this variability [21]. Moreover, differences in training-intensity distribution arise depending on the TIZ method used, because heart rate, pace, and power can yield different zone allocations even when anchored to the same physiological marker [11,12].

The optimal training intensity distribution (TID), and specifically whether endurance training should be considered polarised or non-polarised remains a topic of debate [4,5,8]. It is increasingly recognised that the most appropriate TID likely depends on multiple factors, including the sport, the athlete's physiological characteristics, and the method used to quantify training intensity. It must also be recognised that the TID is an accumulation of power or heart rate in zone which does not directly indicate the physiological effect of the training. As no single "best" TID has been established, tools that describe and compare how training intensity is distributed remain valuable. One such tool is the polarisation index [22], which is based on a three-zone model (Zone 1 (Z1), Zone 2 (Z2), Zone 3 (Z3)) where the proportions of all zones equal 100%. These proportions are entered into the index which applies a logarithmic function to produce an output in arbitrary units reflecting the balance of training across zones 1–3. Values > 2 indicate a polarised distribution, requiring, by definition and by the constraints of Equation 1, that the proportion of Z3 exceeds that of Z2, whereas values < 2 indicate a non-polarised distribution. Importantly, the index does not simply classify training as polarised or non-polarised, the magnitude of the score reflects the degree of polarisation. While useful for summarising relative intensity distribution, the index has several limitations. Notably, it does not incorporate total training volume, and the choice of training-zone-demarcation method can significantly impact the outcome [22].

$$Polarisation\ Index = log_{10}\frac{\text{Zone 1}}{\text{Zone 2}}\cdot\text{Zone 3} \times 100 \quad (1)$$

Regardless of how training zones are demarcated, TIZ data alone cannot indicate whether athletes are working at the upper or lower end of a given zone. In elite-level cyclists, it is common for markers of the first lactate or ventilatory threshold to be well above

the typical intensity of Z1, where most training and racing time is accumulated [23,24]. Conversely, markers of the second lactate or respiratory compensation point are significantly below power at $\dot{V}O_{2\,max}$ and power outputs achieved during extreme-intensity efforts [25]. Using the mean lactate-based zones of professional cyclists reported by Sanders and Heijboer [24] as an example, a cyclist coasting downhill at 0 W and riding at 300 W would both be classified Z1, despite the clear physiological differences between the two efforts. Likewise, time spent at 360 W and time spent sprinting above 1000 W would both fall within Z3, even though the metabolic demands differ significantly [26]. Increasing the number of training zones is one option to further refine TID analysis [27], but every zone will still contain a high and low end that cannot be distinguished using a TIZ approach.

Power meters are now commonplace on the bikes of both amateur and professional cyclists, with most commercial devices demonstrating good precision [28]. Unlike many other sports, cyclists can quantify both internal workload (heart rate) and external workload (power), while cross-referencing the two for a more complete picture of the demand. Power measurement also enables the calculation of total work completed during a ride, as shown in Equation (2).

$$Work\ (\mathrm{kJ}) = \frac{Power\ (\mathrm{W}) \times Time\ (\mathrm{s})}{1000} \quad (2)$$

Using this relationship, it is possible not only to quantify total work, but also to calculate the work accumulated within specific training zones. This may provide a more refined method of characterising training intensity distribution, since work accumulates more rapidly at the higher end of a zone than at the lower end, even when the time spent in the zone is identical.

Therefore, the aim of this study is to analyse training and racing data from well-trained cyclists to compare training intensity distribution derived from TIZ and work-in-zone (WIZ) data. Although substantial differences in zone proportions are expected between the two methods, the purpose of the study is not to position one as superior. Instead, the goal is to introduce a complementary approach to training intensity distribution analysis that practitioners, scientists, and athletes can use alongside existing methods to enhance their understanding of endurance training.

2. Materials and Methods

2.1. Participants and Procedures

Twelve male cyclists (Age, 26.9 ± 4.6 years) agreed to participate in the study. Based on the participant classification framework outlined by McKay et al. [29], nine were classified as Tier 3 (highly trained), two as Tier 2 (international-level), and one as Tier 1 (World Class). All cyclists had a minimum of 3 years of training history. The study spanned a 26-week period divided into two phases. The first phase ("training period") comprised 25 weeks of training, followed by the second phase ("race period") which consisted of a 7-day elite international stage race (Tour of Southland, New Zealand). The study was approved by the University Human Ethics Committee, and all participants provided written informed consent prior to involvement.

Throughout both phases, participants recorded power output (1 Hz) during all training sessions and race stages using their own cycling computers (set to 1 s recording) and power meters (SRM origin (SRM, Jülich, Germany), SRM DA-9000 (SRM, Jülich, Germany), Favero Assioma Duo (Favero Electronics, Arcade, Italy), Quarq AXS (SRAM, Chicago, USA), FSA Powerbox (FSA, Milan, Italy)). All participants were instructed to perform a zero offset via their bicycle computer prior to each ride. Participants were instructed to advise the research team if they changed power meters, or if there were any known problems or periods where power data was not collected. Substantial missing data or changing power meter models

would result in exclusion from the study. There were no rides with obviously incorrect data nor any missing data from included participants; however, one participant (the overall race winner) was removed from the study due to not having a working power meter during the race.

All logged data were uploaded to an online endurance training and performance management platform (TrainingPeaks, Louisville, CO, USA) from their personal devices. The data were then exported and analysed using desktop-based training-analysis software (WKO5+, build 587, Louisville, CO, USA) to determine TIZ and WIZ according to Equation (2).

A three-zone model (Z1, Z2, Z3) was applied [22]. Due to athletes being based in many different cities and countries it was not possible to do laboratory-grade physiological testing; therefore, the boundary between Zones 2 and 3 was defined as 95% of the peak 20 min power observed in the complete 26-week dataset [1,15,30], while the boundary between Zones 1 and 2 was set at 85% of this intensity [15,16]. The polarisation index for power data was calculated for both TIZ and WIZ models according to Equation (1) [22].

2.2. Statistical Analysis

Descriptive data (mean ± SD) were calculated for the 20 min power, zone-demarcation points, total training-period and race-period volume and work, polarisation index, and TIZ and WIZ values. Differences in polarisation index were analysed using a two-way repeated measures ANOVA with method (TIZ vs. WIZ) and context (training vs. racing) as within-participant factors. Where significance was found, Sidak's post hoc multiple comparison testing was performed.

The three intensity zones (Z1, Z2, Z3) form a closed composition, with each zone expressed as a proportion of total TIZ or WIZ. As these proportions always sum to 1, any change in one zone necessarily constrains the others. These dependencies violate the assumptions of standard statistical methods that treat variables as independent and unconstrained [6,7]. Consequently, analysing the raw proportions can therefore lead to invalid inferences [6,7]. To address this, all zone-based data were analysed using compositional data analysis (CoDA).

Compositions were transformed using an isometric log-ratio (ILR) transformation, producing two orthogonal coordinates (ILR-1 and ILR-2). In this ILR basis, ILR-1 represents the balance in zone distribution between Z1 and the combined higher-intensity zones (Z2 + Z3). Higher ILR-1 values indicate a relatively greater proportion of Z1, whereas lower values indicate a relatively greater proportion of Z2 + Z3. ILR-2 reflects the relative balance between Z2 and Z3, with higher values indicating a relatively greater proportion of Z2 and lower values indicate a relatively greater proportion of Z3.

Prior to model fitting, normality of ILR-1 and ILR-2 was assessed using the D'Agostino–Pearson test, and no violations were detected.

ILR-1 was analysed using a linear mixed-effects model with context (training vs. racing) and zone type (TIZ vs. WIZ) as fixed effects, and participants as a random intercept. ILR-2 was analysed using the same fixed-effects structure but without a random intercept, as between-participants variance in ILR-2 was negligible.

This approach allows inference on how compositions shift across conditions while accounting for repeated measures within participants. Estimated marginal means (M) were obtained for each factor level and interpreted in relation to the underlying compositional structure. To complement the ILR-based statistical analysis, the three-part composition was visualised using ternary plots, with paired TIZ and WIZ points, centroids, and arrows illustrating the direction and magnitude of compositional shifts within the geometric space.

Descriptive and two-way ANOVA were performed using Graphpad Prism (V7.0). CoDA was performed using Matlab (R2022b, MathWorks Inc., Natick, MA, USA), while statistical analysis of ILR-1 and ILR-2 using a linear mixed-effects model was performed in SPSS version 29.

3. Results

Post-collection mean ± SD 20 min peak power was 376 ± 16 W, with Z1-Z2 and Z2-Z3 demarcation points of 303 ± 13 W and 357 ± 15 W, respectively. During the training period, participants completed 365.2 ± 85.4 h of cycling, distributed as 311.5 ± 77.2 h (85.10 ± 4.18%) in Z1, 27.6 ± 8.3 h (7.63 ± 1.8%) in Z2, and 26.2 ± 9.9 h (7.26 ± 1.60%) in Z3 (Figure 1A). In the race period, total volume was 22.9 ± 1.2 h, comprising 15.4 ± 1.4 h (67.11 ± 3.91%) in Z1, 2.5 ± 0.4 h (10.85 ± 2.02%) in Z2, and 5.0 ± 0.8 h (22.05 ± 3.37%) in Z3 (Figure 1B). Total work performed was 278,305 ± 68,774 kJ during the training period and 19,534 ± 1151 kJ during the race period. Work distribution in the training period was 204,990 ± 56,894 kJ (73.38 ± 7.15%) in Z1, 32,266 ± 9972 kJ (11.65 ± 2.58%) in Z2, and 41,049 ± 15,426 kJ (14.97 ± 5.14%) in Z3 (Figure 1A), while in the race period it was 8083 ± 1041 kJ (41.42 ± 5.15%) in Z1, 2933 ± 513 kJ (14.99 ± 2.22%) in Z2, and 8518 ± 1404 kJ (43.58 ± 6.44%) in Z3 (Figure 1B).

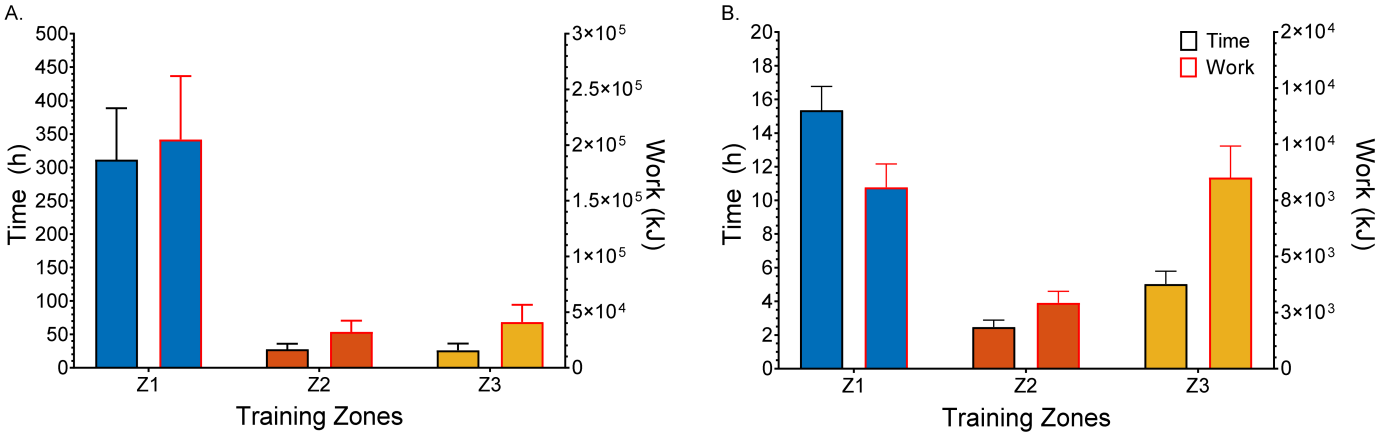


Figure 1. Mean ± SD for zone-distributed TIZ and WIZ during the 25 weeks of training (**A**) and 1-week race (**B**).

Mean weekly training volume (derived from total training hours divided by 25 weeks) was 14.61 ± 3.42 h·wk^{-1}, whereas race-week volume was 22.86 ± 1.20 h·wk^{-1}. Mean weekly training work, derived from total work accumulated over the training period, was 11,132 ± 2751 kJ·wk^{-1}, compared with 19,534 ± 1151 kJ·wk^{-1} during the race week.

Weekly time in each zone during the training period averaged 12.46 ± 3.09 in Z1, 1.10 ± 0.33 in Z2, and 1.05 ± 0.4 in Z3, whereas during the race week the corresponding values were 15.36 ± 1.41 h, 2.47 ± 0.41 h, and 5.03 ± 0.76 h (Figure 2A).

Weekly work distributed followed a similar pattern during the training period where participants accumulated 8200 ± 2276 kJ·wk^{-1} in Z1, 1291 ± 399 kJ·wk^{-1} in Z2, and 1642 ± 617 kJ·wk^{-1} in Z3, whereas during the race week they accumulated 8083 ± 1041 kJ, 2933 ± 513 kJ, and 8518 ± 1404 kJ in Z1, Z2, and Z3, respectively (Figure 2B).

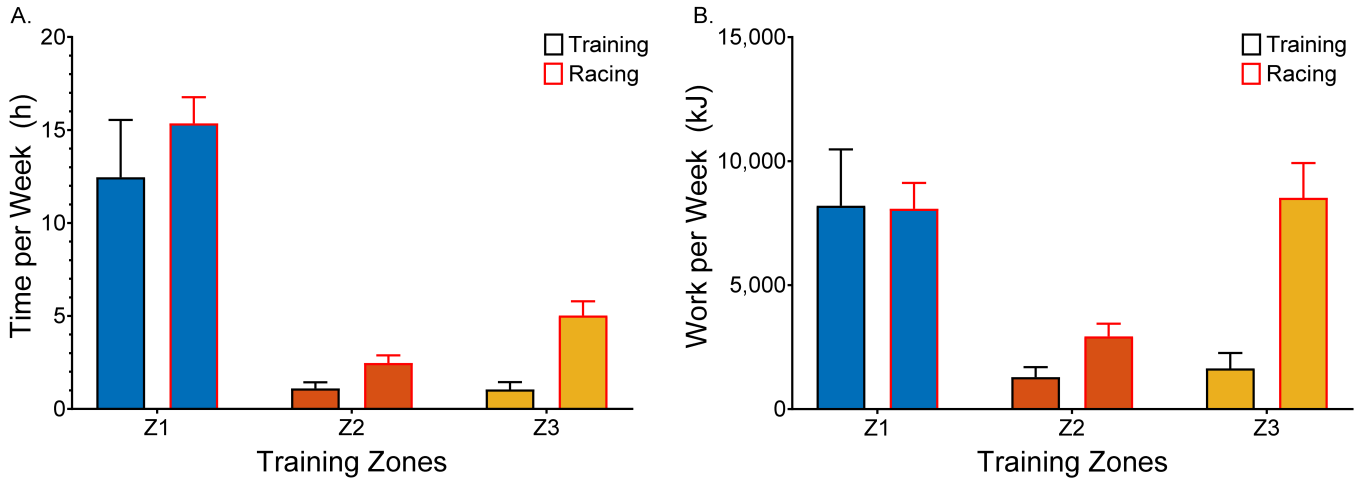


Figure 2. Mean ± SD weekly hours (**A**) and weekly work (**B**) accumulated in each training zone during the 25-week training period and 7-day race period.

Two-way ANOVA for the polarisation index data showed a significant interaction for context × method ($F_{(1,11)}$ = 181.5, $p < 0.0001$) with a main effect of context ($F_{(1,11)}$ = 57.72, $p < 0.0001$). There was no main effect of method ($F_{(1,11)}$ = 0.1174, p = 0.738). Post hoc testing indicated differences between racing and training polarisation scores for both TIZ ($p < 0.0001$) and WIZ ($p < 0.0001$). Mean ± SD polarisation index values were 1.90 ± 0.09 for TIZ and 1.96 ± 0.10 for WIZ during training, and 2.14 ± 0.01 for TIZ and 2.08 ± 0.08 for WIZ during racing, illustrating a larger TIZ-WIZ separation in the race period.

A linear mixed-effects model with random intercepts for participants examined the effects of context (training vs. race) and Zone Type (TIZ vs. WIZ) on the ILR-transformed data. Both ILR-1 and ILR-2 passed the D'Agostino–Pearson normality test (K2 = 3.848, p = 0.146; K2 = 2.614, p = 0.271).

ILR-1 reflects how the composition is distributed between Z1 and the combined higher intensity zones (Z2 + Z3). Higher ILR-1 values indicate a composition with proportionally greater Z1, whereas lower values indicate relatively greater proportions of Z2 + Z3. For ILR-1, there were significant main effects of context ($F_{(1,44)}$ = 212.09, $p < 0.001$) and zone type ($F_{(1,44)}$ = 123.21, $p < 0.001$), with no interaction ($F_{(1,44)}$ = 2.914, p = 0.095). Estimated marginal means indicated higher ILR-1 values during training (M = 1.724, 95% CI: 1.383–2.066) than racing (M = 0.802, 95% CI: 0.460–1.143), and higher values in TIZ (M = 1.614, 95% CI: 1.273–1.956) than WIZ (M = 0.911, 95% CI: 0.570–1.253). Sidak's pairwise comparisons confirmed both main effects ($p < 0.001$).

ILR-2 describes how the composition is distributed between Z2 and Z3. Higher ILR-2 values indicate relatively more Z2, whereas lower values indicate relatively more Z3. For ILR-2, there were significant main effects of context ($F_{(1,45)}$ = 137.4, $p < 0.001$) and zone type ($F_{(1,5)}$ = 22.1, $p < 0.001$). No interaction term was included because ILR-2 represents the orthogonal Z2-Z3 contrast and the centroid shifts indicated parallel patterns across context (training vs. racing). Estimated marginal means indicated lower ILR-2 values during racing (M = −0.629, 95% CI: −0.699 to −0.559) than training (M = −0.051, 95% CI: −0.121–0.019), and higher values for TIZ (M = −0.224, 95% CI: −0.294 to −0.154) than WIZ (M = −0.456, 95% CI: −0.526 to −0.386).

Together, ILR-1 and ILR-2 describe the full three-zone distribution and are consistent with the centroid shifts observed in Figure 3B,D.

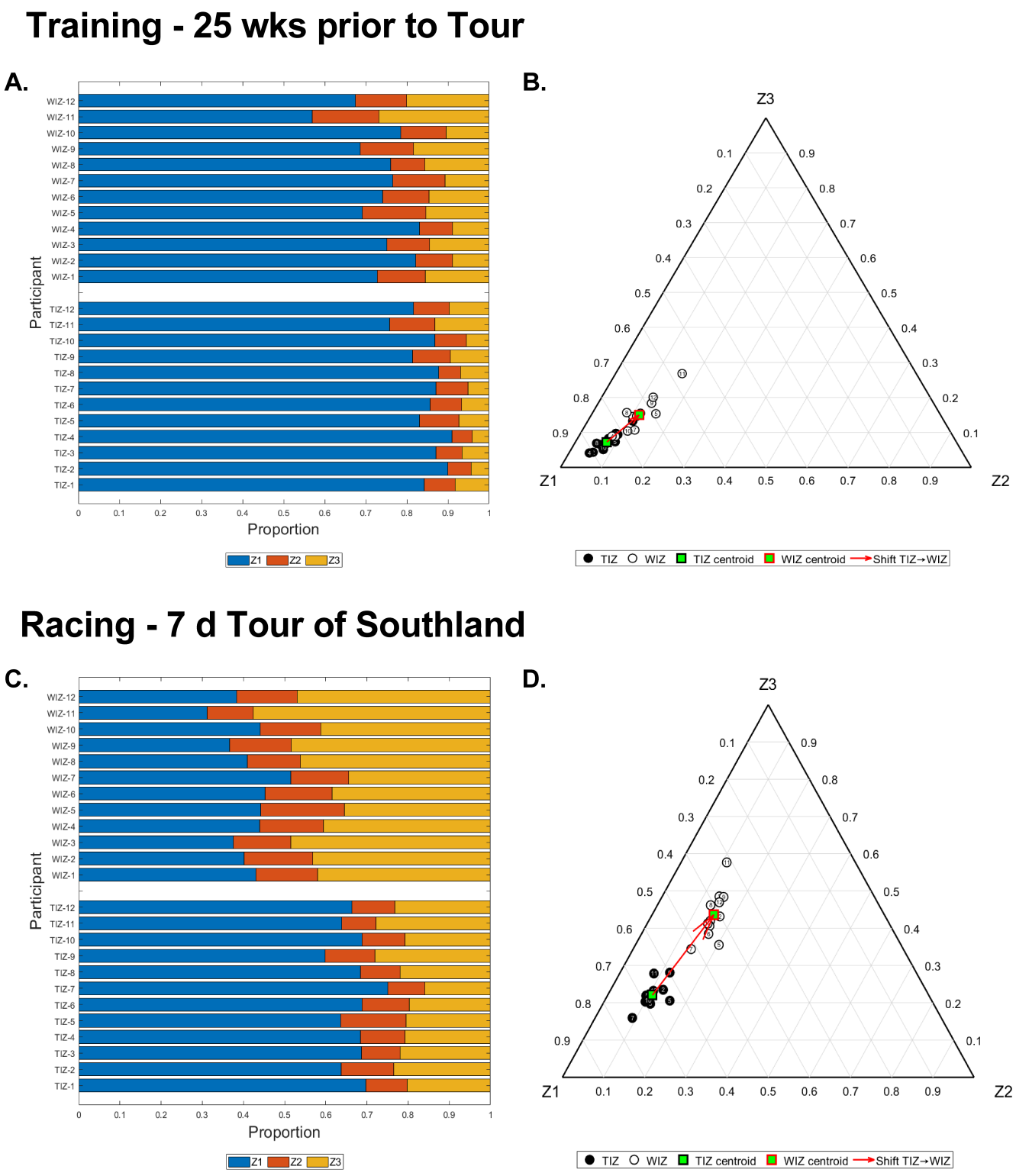


Figure 3. Individual participant training TID (**A**) and corresponding ternary plot (**B**), and racing TID (**C**) and corresponding ternary plot (**D**). In the ternary plots, each participant (numbered markers) contributes paired TIZ and WIZ compositions. Centroids represent the group mean TIZ and WIZ compositions, and the arrows connecting the centroids illustrate the overall group-level shift direction of change from TIZ to WIZ. Movement towards a vertex reflects a greater relative contribution of that zone (Z1 bottom left, Z2 bottom right, and Z3 top), while movement along an edge reflects redistribution between adjacent zones.

4. Discussion

The purpose of this study was to introduce a novel method of training intensity distribution analysis (WIZ) and compare it to the commonly used TIZ method in high performance cyclists. A further aim was to examine how these methods may yield differing or complementary insights into the demands imposed during training compared with high-level competition. The main findings were that racing, when examined over a weekly period, showed substantially higher overall volume and intensity than the cyclists' typical training. This pattern was supported by the polarisation index, which showed a context-specific shift towards greater polarisation and increased Z3 during racing, although TIZ and WIZ did not differ significantly in their polarisation index values. Similarly, the compositional data analysis ILR-1 and ILR-2 coordinates both indicated a redistribution towards Z2-Z3 during racing. ILR-1 values were lower in racing than training, reflecting reduced Z1 and greater Z2 + Z3, while ILR-2 values were also lower in racing, indicating a shift from Z2 towards Z3. Both ILR coordinates were strongly influenced by the intensity distribution method (TIZ or WIZ), with WIZ consistently shifting the composition toward greater Z2 + Z3, and specifically Z3 allocation. Overall, the demands of the stage race were substantially higher in both intensity and volume than the average week of the preceding 25 weeks of training. WIZ was also more sensitive than TIZ in capturing these differences, particularly during racing.

The participants in this study ranged from highly trained to international-level, with 20 min power and weekly training volumes consistent with values reported for professional road cyclists [15,31]. Their power-based training-period TIZ distribution closely matched that reported in similar cohorts [11], and the race-period TIZ distribution aligned closely with patterns reported in mountain stages at elite level [32]. Taken together, these characteristics indicate that our sample is representative of Tier 1–3 high-level athletes [29], with training and racing intensity distributions typical of cyclists at this performance level.

The results highlight clear limitations of TIZ when applied to power-based data. In the training period, TIZ produced a much greater proportion of Z1 than WIZ (Figure 3B), despite both methods being applied to the same underlying dataset and the TIZ distribution being typical for cyclists of this level [11]. This discrepancy was even more pronounced in racing (Figure 3D), where WIZ produced nearly twice the proportion of Z3 (43.58%) compared with TIZ (22.05%). Together, these differences illustrate how WIZ captures the accumulation of high-intensity work more effectively than TIZ, particularly when large amounts of Z3 are performed during racing [13].

Despite these changes in intensity distribution between the zone types, no significant differences between TIZ and WIZ were revealed when calculating the polarisation index, with both methods producing a non-polarised PI, where TIZ = 1.90 and WIZ = 1.96 [22]. As such, the training-period TIZ distribution in the present study followed the pyramidal pattern typically reported in endurance athletes [5], characterised by a predominance of Z1 with smaller proportions of Z2 and Z3.

Comparing training and racing contexts revealed significant differences in polarisation index, with racing exceeding the 2.0 threshold for both TIZ (PI = 2.14) and WIZ (PI = 2.08). This reflects the higher demands typically associated with competition [32,33]. However, interpreting these values in isolation is limiting because the polarisation index reflects only relative proportions and does not account for substantially greater total work and time accumulated during the race week [22,34]. In this study, Z3 increased substantially during racing, but concurrent increases in Z2 and reductions in Z1 meant the polarisation index changed little, despite large differences in high-intensity work. In this instance, the compositional approach provides a clearer representation of these changes, by distinguish-

ing whether differences arise from time spent in a zone or from the magnitude of work accumulated within it.

As such, ILR-1 values were higher for training than racing, indicating a relatively greater proportion of Z1 in the overall composition, whereas lower ILR-1 values reflected a shift towards greater allocation to Z2 + Z3. This pattern was more pronounced when using WIZ, which accumulates work more rapidly in higher zones due to its linear scaling with power (Equation (2)). ILR-2 further showed that racing shifted the balance of high-intensity work towards Z3 relative to Z2, consistent with previous analyses of elite-level cycling races [35].

Taken together, the lower ILR-1 and ILR-2 values during racing indicate a clear shift towards the higher intensity zones, a pattern reinforced by the displacement of the ternary plots' centroids (Figure 3B,D). These findings highlight that differences between training and racing arise from both the volume of high-intensity work and the manner in which the work is accumulated. Incorporating a work-based metric alongside duration-based analysis therefore provides a more complete representation of the demands of each context, particularly given the established importance of total work and its intensity for cycling performance and durability [32,36].

While these findings clarify how both context (training vs. racing) and zone classification method (TIZ vs. WIZ) influence intensity distributions derived from power output data, several methodological limitations warrant consideration.

Several assumptions underpin our zone-demarcation approach and the implementation of WIZ, and these should be acknowledged. Although the same approach to demarcating zones as used in previous research was used here [1,14,30], it cannot be verified that the power data represented an absolute all-out effort or the athletes' true maximal capabilities. Nor can we verify the consistency of each and every power meter. Nonetheless, the aim of this study was not to evaluate the performance implications of training zone distributions using WIZ, but rather to introduce and illustrate this novel work-based metric using our dataset. Therefore, although our method to determine the zone demarcations is unlikely to alter the qualitative patterns observed, it may produce different absolute intensity distributions compared with zones derived from all-out power tests or laboratory assessments. Likewise, our sample size of 12 male elite athletes also limits the extent to which these findings can be generalised across different levels of racing and types of racing (e.g., stage races vs. one-day races). Future research using zones defined from established physiological markers, such as critical power [37], lactate thresholds, or ventilatory thresholds [38], would help validate and extend the concepts presented in this study.

A more pressing limitation in the application of the WIZ concept relates to its connection with physiology and the inherently dynamic nature of physiological intensity. Power, work, and time have long been central to cycling performance analysis [39], with the concept of durability, how prior work shifts the power–duration relationship, receiving increasing attention in recent years [40–42]. It is well established that factors such as prior work [43], heat [44,45] and altitude [46,47] acutely reduce the physiological response to exercise and alter the power associated with any given physiological intensity. It is also reasonable to expect physiological differences between a sustained effort at a given intensity and an intermittent workload totalling the same TIZ or WIZ within a zone. Ideally, intensity-distribution analysis would incorporate methods capable of capturing this dynamic physiological intensity in real time, rather than relying solely on mechanical outputs.

Heart rate may appear useful in this regard, as it remains relatively stable at key physiological markers even when mechanical power fluctuates [46]. However, heart rate is also influenced by external factors such as caffeine intake, which can have mixed effects depending on exercise intensity [48,49], and fatigue [20], limiting its utility in this situation.

The present study introduces WIZ as a tool that can enhance understanding of what was done and what the demands were, but it should be recognised that when large amounts of high-intensity work are performed, as observed during racing, the true physiological cost may be even greater than mechanical data alone due to the disproportionately fatiguing nature of this intensity zone [36]. Together, these considerations highlight that while WIZ provides valuable insight into the mechanical demands of training and racing, the physiological intensity associated with those demands is inherently dynamic, and a more holistic approach warrants further exploration.

5. Conclusions

This study compared a novel training intensity distribution method (WIZ) with the traditional time-in-zone (TIZ) method in highly trained cyclists across training and racing contexts. Both the method used and the context markedly altered the resulting intensity distributions. WIZ consistently shifted the distribution towards higher intensity zones, an effect that was amplified during racing, where overall load was also greater. Although the two methods produced similar polarisation index values, compositional analysis revealed meaningful differences in how intensity was distributed, with racing showing a clear redistribution from Z1 towards Z2 + Z3 and, within the higher intensity domain, from Z2 toward Z3.These findings highlight limitations of TIZ, particularly its inability to account for the magnitude of intensity within a zone, whereas WIZ captures this through the relationship between power, time, and work. Neither method alone provides a complete picture of training or racing demands but using them together may improve the evaluation of training programmes and the understanding of race demands, especially regarding high intensity distribution. Future work should integrate mechanical and physiological measures within similar analytical frameworks to further advance understanding of athlete demands.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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Conflicts of Interest: The authors declare no conflicts of interest.

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