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Monitoring Endurance Adaptations Through Critical Speed and Work Capacity (D′) in Youth Amateur Football Athletes

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ABSTRACT

This study examines athletic performance using two physiological markers: critical speed (CS) and critical power (CP), which describe the relationship between exercise intensity and duration—particularly pertinent to non-cyclic sports such as football. Twenty amateur male football players (age: 18 years) participated in three testing sessions over a three-month period. Each session involved time-trial runs of 3, 6, and 12 minutes. For each trial, distance covered, and end-exercise heart rate were recorded. CS, and the work capacity above CS (D′) were estimated using three modeling approaches: linear, hyperbolic, and inverse-time (1/time) models. The estimated CS values did not differ significantly between models, suggesting consistency across mathematical approaches. Notably, CS increased significantly over the three sessions ($p < 0.001$), indicating improved aerobic fitness over time. In contrast, D′ exhibited a decreasing trend, reaching statistical significance in the hyperbolic model. This reduction may reflect diminished tolerance to high-intensity efforts despite improved aerobic capacity. These findings support the utility of CS as a stable and sensitive marker of endurance performance, while highlighting the greater variability and possible context-dependence of D′.

Keywords: **Endurance Adaptations, critical speed, Work capacity (D')**

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INTRODUCTION

Sport performance is considered to be the result of factors related to the athlete themselves (morphological and biological dimensions) as well as their practice (biomechanical and psychomotor dimensions, along with the environment). Performance is directly linked to its objective, as many authors consider it to be a method of evaluation (Benoit et al., 2009). Physiological capacities, such as motor performance, can influence physical fitness (Miln et al., 2021). understanding the biomechanical factors in sprinting is useful due to their critical value for performance (Mero et al., 1992). Cyclic sports require repetitive movements, typically lasting more than five minutes, with a primarily aerobic metabolism. When an endurance athlete engages in high-intensity efforts, various physiological factors limit their performance, such as maximal oxygen consumption, first and second ventilatory thresholds, energy efficiency, and economy (Lorenzo Calvo et al., 2020). The section on establishing a power-duration relationship presents the existing concepts of power-duration models alongside the exercise intensity domains. It is also recommended to avoid single effort prediction trials, such as functional threshold power (Leo et al., 2022). In this case, we are talking about maximal average power, which has numerous supporting points working in the domain of many biological and technical factors. One solution is to use mathematical models to define the power-time relationship. Ideally, this model predicts performance accurately across all exercise intensity domains and the of performance-oriented systems (Puchowicz et al., 2020). Critical power (CP), the asymptote of the power-duration relationship, is a fundamental concept in sports science and exercise physiology. Since CP defines the boundary between intense and severe exercise intensities, exercise below the CP is characterized by a stable metabolic state, while exercise above the CP leads to continuously increasing oxygen consumption rates (VO2), blood lactate concentrations, and accelerated fatigue of performance (van Rassel et al., 2024). The concept of critical speed (CS) has also been applied to various sports, although rowing and swimming have been specific applications for predicting performance. Thus, while it is true that the speed-duration relationship can provide estimates for both aerobic and anaerobic systems (D'), studies focusing on performance prediction for distances ranging from 400m to 10,000m are rare. This situation is surprising given that, at these distances, reports indicate that both systems contribute significantly (Nimmerichter et al., 2017). The relationship between exercise intensity (e.g., running speed or power) and the tolerable duration in

the domain of severe exercise can be characterized by a hyperbolic function (Hunter et al., 2023 ; Muniz-Pumares et al., 2019 ; Poole et al., 1988). The asymptote, critical speed, or critical power (CS/CP) are generally accepted to indicate the transition from the heavy exercise domain to the severe exercise domain (Hunter et al., 2023 ; Jones et al., 2010). Therefore, although CS/CP seems to represent a metabolic rate rather than necessarily a single external mechanical output (power or speed) (Hunter et al., 2023 ; Barker et al., 2006). The CS parameter indicates a robust fatigue threshold that separates sustainable running speeds from unsustainable ones, or the "heavy" and "severe" domains of high- intensity exercise (Kramer et al., 2019 ; Poole et al., 2016). The maximal effort test method was established to estimate critical speed (CS) and the curvature constant D'. Although this method has recently been validated for shuttle running, it is currently not well understood in the context of linear running (Kramer et al., 2019). High-intensity running is defined by the relationship between short-duration efforts and Tlim tests, which is hyperbolic (Kramer et al., 2019). From Tlim (x-axis) associated with running different distances (y-axis), once the D'-Tlim is plotted and intercepted, the CS (slope, critical speed) and the finite capacity for running speeds above CS can be determined — or D', the intercept itself (that is, the distance–Tlim model, or D'-Tlim)(Fukuba & Whipp, 1999) . Two- or three-parameter mathematical models have been used to assess both linear and non-linear CS and D' (Jones et al., 2010). CS and D' are generally calculated from 3 to 5 exhaustive running trials conducted over several days, which is very time-consuming and interferes with athletes' training. Moreover, several characteristics related to treadmill and track running — such as propulsion, air and inertial resistance, and gait pattern — have been reported, noting that these factors could impact the applicability of treadmill-based measurements to field conditions (Van Caekenberghe et al., 2013 ; Morin et Sève, 2011). It has been shown that CS obtained from a single-visit field test was not significantly different from the traditionally used multi-visit laboratory test, thereby validating the findings of these studies for use with competitive athletes (Galbraith, Hopker, Lelliott, et al., 2014). Evidence is still needed to determine whether performance in running can be predicted from a single-visit laboratory test in athletes using three commonly used mathematical models. These include the hyperbolic speed–distance model, the linear distance–time model, and the linear speed–inverse time model (Galbraith, Hopker, Lelliott, et al., 2014). The primary objective of this study is to examine the temporal and spatial (time/distance) evolution of variations in critical speed

(CS) and the work capacity above CS (D', corresponding to the effort beyond critical speed). This analysis aims to identify the most relevant model for predicting performance in athletes participating in cyclical sports, such as football.

2. Method and Materials

2.1 Participants

Twenty amateur football players, all male and in good health, belonging to the under-19 category of the Sidi Moussa Sports Club (CSSM), which competes in the regional division of the Algiers Wilaya Football League in Algeria, took part in this study. The team's coach served as the principal researcher. The participants were informed of the study protocol, and their participation was conditional upon signing an informed consent form. This form was also signed by their parents and validated with the official stamp of the club president. The participants had an average age of 17 ± 4 years (mean ± standard deviation), an average height of 173 ± 2 cm, and an average weight of 65 ± 7 kg. Their average BMI was 21.8 ± 1.29, with an average MAS (maximum aerobic speed) of 14 ± 47 for session 1 (S1) and 15 ± 12 for session 3 (S3). Their average VO2max was 50.7 ± 3 for S1 and 52.9 ± 2.37for S3.

2.2 Materials

The testing was conducted on a 200-meter outdoor running track, set up with cones on a football field and measured with a measuring tape. A Kalenji BT device was used to record speed and heart rate data. The EXphysLab software was used to calculate the parameters of critical speed (CS) and work capacity above CS (D'), applying three different models: linear, hyperbolic, and inverse time (s^{-1}).

2.3 Design and Procedure

The study spanned a period of three months, with one session per month (a total of three sessions). The first session took place from September 17 to September 21, 2024; the second from October 17 to October 21, 2024; and the third from November 16 to November 20, 2024.In each session, participants performed three running trials of 3, 6, and 12 minutes each. The trials were carried out on the prepared 200-meter track. Each run was followed by a 48-hour rest period. During these trials, the athletes were instructed to run either

until exhaustion or until the end of the allotted time. For each cycle, the distance covered and the players' heart rates at the end of the effort were recorded.

2.4 Statistical Analysis

An analysis of variance (ANOVA) was used to examine the data related to Critical Speed (CS) and work capacity above CS (D'). This statistical method is designed to compare means across multiple groups and determine whether statistically significant differences exist between them. In this study, repeated measures ANOVA was applied, as multiple measurements were collected from the same group of participants under different spatio-temporal conditions. Following the ANOVA, post hoc analyses were conducted to identify the specific time points or groupings responsible for the observed differences in sample means. These post hoc tests allowed for a more detailed examination of the data by pinpointing when or under what conditions significant changes in CS and D' occurred. This process aimed to detect any statistical disparities among the repeated measures and to reveal which periods or conditions had the greatest influence on the target variables.

3. Results

Sample

	N	Mean ± SD (m/s)	Max - Min
Age	20	17.4 ± 0.50 (y)	17 ± 18
Weight	20	65.7 ± 4.27 (	58 ± 72.5
Height	20	1.73 ± 0.05	1.65 ± 1.84
BMI	20	21.8 ± 1.29	19 ± 23
VO2max S01	20	50.7 ± 3	45.5 ± 56.3
VO2max S03	20	52.9 ± 2.37	49 ± 57.4

3.1 Comparison of Critical speed's model's output

3.1.1 Critical speed

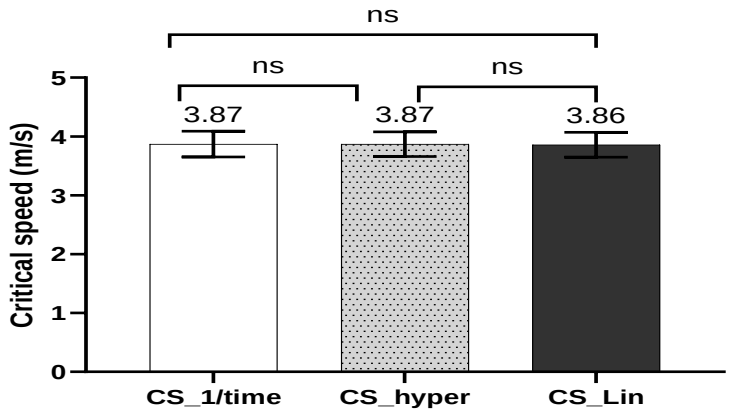
Table 1. Comparison of the three methods ANOVA

	N	Mean ± SD (m/s)	Max - Min	F	P-Value	Sig
CS_1/time	60	3.87 ± 0.218	3.38 - 4.31			
CS_hyper	60	3.87 ± 0.209	3.38 - 4.31	0.527	0.592	Ns
CS_Lin	60	3.86 ± 0.212	3.38 - 4.31			

Based on the one-way analysis of variance (ANOVA) presented in Table 1, the three

methods for estimating critical speed—CS_1/time, CS_hyper, and CS_Lin—yielded extremely similar results. The mean values across the methods were nearly identical, with a maximum difference of only 0.01 m/s, and the standard deviations were also very close (approximately 0.21 m/s). All methods shared the same range of values (0.93 m/s between the minimum and maximum). The ANOVA, which assesses whether there are significant differences between group means, produced a very low F-value (0.527), indicating minimal variance between groups relative to within-group variance. The corresponding p-value was 0.592, well above the conventional significance threshold of 0.05, confirming that the differences observed were not statistically significant. The notation "NS" (not significant) in the table further supports this conclusion. Overall, the results indicate that the three methods provide statistically equivalent estimates of critical speed, with no method showing clear superiority. Therefore, any of the three can be used interchangeably in this context.

Figure 1. Critical Speed Comparison Between Methods



The graph clearly illustrates a comparison of mean critical speeds across the three methods. The "ns" annotations above the bars indicate that no statistically significant differences were found, which is confirmed by the ANOVA result ($p = 0.592$). Additionally, the error bars representing the standard deviations are visually very close one another, highlighting the homogeneity of the results across the methods.

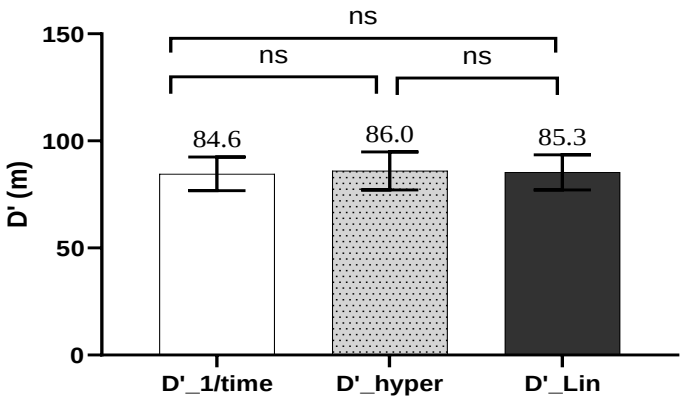
2.1.2 D prime

Table 2. Comparison of the three methods ANOVA

	N	Mean ± SD (m)	Min - Max	F	P-Value	Sig
D'_1/time	60	84.6 ± 7.89	56.4 - 108			
D'_hyper	60	86 ± 8.89	58.7 - 112	2.29	0.106	Ns
D'_Lin	60	85.3 ± 8.24	57.5 - 108			

Based on the one-way analysis of variance (ANOVA) presented in Table 2, the three methods for estimating D′ yielded relatively similar results. The D′ value for the 1/time model was slightly lower (84.6 m) compared to the hyperbolic model (86 m), with the linear model (D′_Lin) falling in between (85.3 m). The variability, as indicated by the standard deviations, was comparable across all methods. The ANOVA, which tests for statistically significant differences between group means, produced an F-value of 2.29, which is relatively low. The corresponding p-value of 0.106 is greater than the conventional threshold of 0.05, indicating no statistically significant differences between the three methods. The "NS" (not significant) notation in the table further confirms this interpretation. Although the p-value was not significant, it is relatively close to the threshold of 0.05, suggesting a slight trend toward a difference. This indicates that with a larger sample size or more sensitive methodologies, significant differences may potentially emerge. Nonetheless, based on these results, the three methods can be considered interchangeable for assessing D′ in this context. However, the proximity of the p-value to the threshold suggests that further investigation could be valuable in future studies.

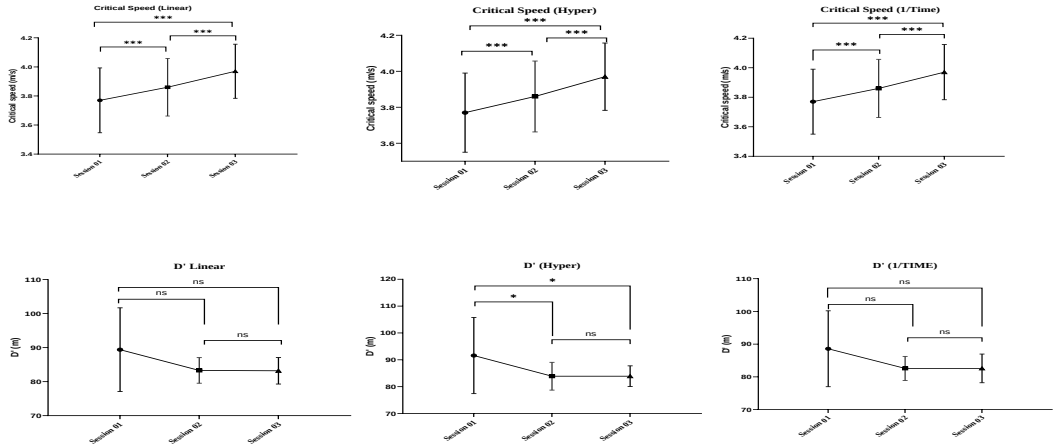
Figure 2. D' Comparison Between Methods



The graph compares the mean D′ values across the three different methods. The "ns" annotations (not significant) indicate that no statistically significant difference was found between the methods, which is confirmed by the ANOVA result ($p = 0.106$). Additionally, the error bars, representing the variability, show similar levels of dispersion across all methods.

3.2 Evolution of the Cs and D'

Figure 3. Changes in Critical Speed and D' Over Three Sessions Across Models



A repeated-measures ANOVA followed by post-hoc comparisons (adjusted) revealed a significant increase in critical speed (CS) across the three sessions for all three calculation models (linear, hyperbolic, 1/time) ($p < 0.001$). Regarding D', a significant decrease was observed only in the hyperbolic model between Session 1 and Session 2 ($p < 0.05$), with no significant changes for the other models.

3.2.1 Critical speed

3.2.1.1 Linear Model

Table 3 Critical Speed (CS) Across Three Sessions Using the Linear Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
CS linear 1	20	3.77 ± 0.223	3.38 - 4.16		
CS linear 2	20	3.86 ± 0.198	3.48 - 4.23	66.1	<0.001
CS linear 3	20	3.97 ± 0.186	3.66 - 4.31		

A repeated-measures ANOVA revealed a significant effect of session on Critical Speed (CS) measured using the linear model ($F(2,38) = 66.1$, $p < 0.001$). Mean CS values increased progressively across the sessions: Session 1 had a mean of 3.77 ± 0.223 m/s (range: 3.38–4.16), Session 2 showed a mean of 3.86 ± 0.198 m/s (range: 3.48–4.23), and Session 3 had a mean of 3.97 ± 0.186 m/s (range: 3.66–4.31). Post-hoc pairwise comparisons with Bonferroni adjustment indicated significant increases between all sessions (Session 1 vs 2, Session 2 vs 3, and Session 1 vs 3; all $p < 0.001$).

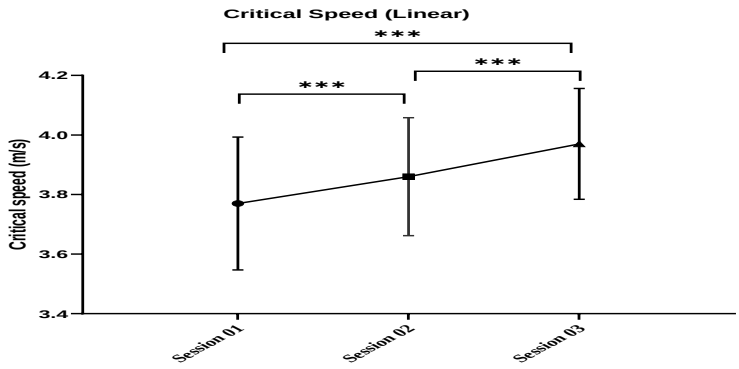
Table 4. Post-Hoc Pairwise Comparisons of Critical Speed Between Sessions Using the Linear Model

Post hoc

Comparison			Mean difference	Standard error	t	p_{tukey}
Session		Session				
S01	-	S02	-0.0935	0.0204	-4.58	< .001
	-	S03	-0.1995	0.0151	-13.24	< .001
S02	-	S03	-0.1060	0.0162	-6.56	< .001

Post-hoc Tukey-adjusted pairwise comparisons for Critical Speed (CS) between sessions using the linear model. Mean differences, standard errors (SE), t-values, and adjusted p-values are presented. All comparisons show significant increases in CS across sessions ($p < 0.001$).

Figure 4. Evolution of Critical Speed Across Three Sessions Using the Linear Model



The figure presents mean ± standard deviation for each session. a clear and progressive increase in Critical Speed over time, with highly significant differences between all sessions

3.2.1.2 Hyperbolic model

Table 5. Critical Speed (CS) Across Three Sessions Using the Hyperbolic Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
CS hyp 1	20	0 ± 3.77	3.78 - 0.22		
CS hyp 2	20	0 ± 3.86	3.86 - 0.197	70.1	<0.001
CS hyp 3	20	0 ± 3.97	3.95 - 0.187		

Values are presented as mean ± standard deviation (SD) and minimum–maximum range. A significant session effect was observed ($F(2,38) = 70.1$, $p < 0.001$), with CS increasing significantly between all consecutive sessions ($p < 0.001$).

Table 6. Post-Hoc Pairwise Comparisons of Critical Speed Between Sessions Using the Hyperbolic Model

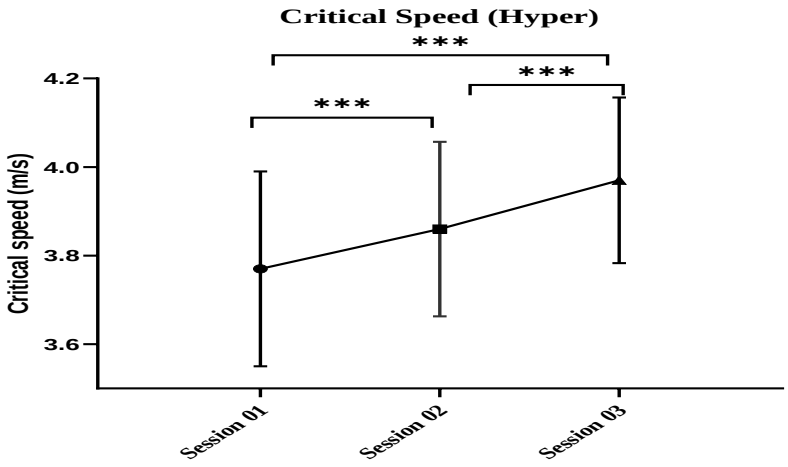
Post hoc

Comparison						
Session		Session	Mean difference	Standard error	t	ptukey
S01	-	S02	-0.0940	0.0203	-4.62	< .001

	-	S03	-0.2010	0.0145	-13.89	< .001
S02	-	S03	-0.1070	0.0156	-6.88	< .001

Post-hoc Tukey-adjusted pairwise comparisons for Critical Speed (CS) between sessions using the hyperbolic model. Mean differences, standard errors (SE), t-values, and adjusted p-values are provided. Significant increases were observed between all sessions ($p < 0.001$).

Figure 5. Evolution of Critical Speed Across Three Sessions Using the Hyperbolic Model



The figure shows mean ± standard deviation for each session. Critical Speed progressively increases over the three sessions, with highly significant differences between all pairs of sessions.

3.2.1.3 1/time Model

Table 7. Critical Speed (CS) Across Three Sessions Using the 1/Time Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
CS 1/time 1	20	3.77 ± 0.228	3.38 - 4.17		
CS 1/Time 2	20	3.86 ± 0.198	3.49 - 4.22	60	<0.001
CS 1/Time 3	20	3.97 ± 0.187	3.66 - 4.31		

Evolution of Critical Speed (CS) across three sessions using the 1/Time model. Values are presented as mean ± standard deviation (SD) and minimum–maximum range. A significant session effect was observed ($F(2,38) = 60.0$, $p < 0.001$), with CS increasing significantly between all consecutive sessions ($p < 0.001$).

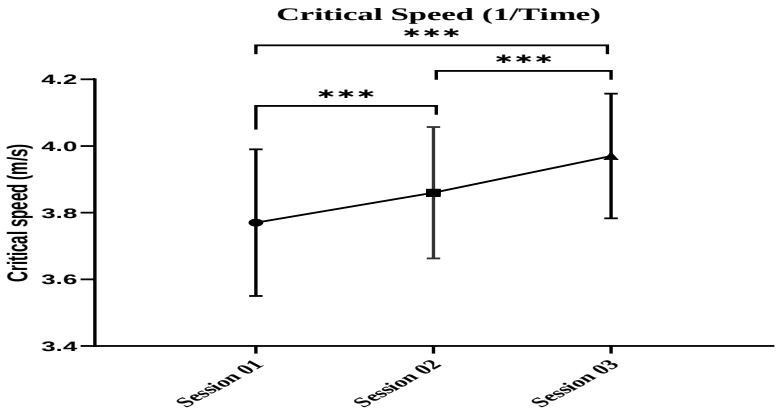
Table 8. Post-Hoc Pairwise Comparisons of Critical Speed Between Sessions Using the 1/Time Model

post hoc

Comparison							
Session		Session		Mean difference	Standard error	t	ptukey
S01	-	S02	-	0.0925	0.0213	-4.34	< .001
	-	S03	-	0.1995	0.0162	12.28	< .001
S02	-	S03	-	0.1070	0.0167	-6.42	< .001

Post-hoc Tukey-adjusted pairwise comparisons for Critical Speed (CS) between sessions using the 1/Time model. Mean differences, standard errors (SE), t-values, and adjusted p-values are provided. All comparisons revealed significant increases in CS between sessions ($p < 0.001$).

Figure 6. Evolution of Critical Speed Across Three Sessions Using the 1/Time Model



The figure presents the mean ± standard deviation for each session, demonstrating a consistent and significant improvement in Critical Speed over time.

3.2.2 D prime

3.2.2.1 Linear Model

Table 8. D' Across Three Sessions Using the Linear Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
D' linear 1	20	89.4 ± 12.3	57.5 - 108	5.08	0.011
D' linear 2	20	83.3 ± 3.76	77.5 - 91		
D' linear 3	20	83.2 ± 3.9	75.5 - 87.5		

Evolution of D' across three sessions using the linear model. Values are presented as mean ± standard deviation (SD) and minimum–maximum range. A significant session effect was observed ($F(2,38) = 5.08$, $p = 0.011$), suggesting a change in D' across sessions.

Table 9. Post-Hoc Pairwise Comparisons of D' Between Sessions Using the Linear Model

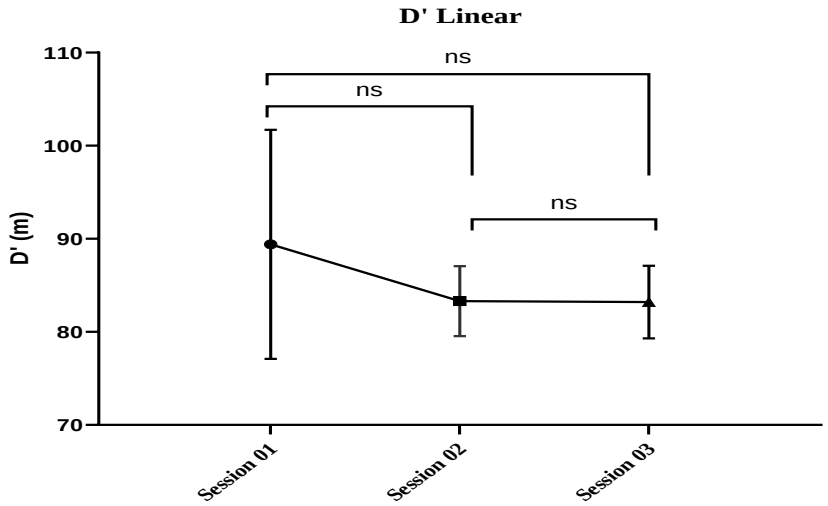
post hoc

Comparison

Session		Session	Mean difference	Standard error	t	p-tukey
S01	-	S02	6.1250	2.680	2.2858	0.082
	-	S03	6.1750	2.658	2.3228	0.077
S02	-	S03	0.0500	0.802	0.0623	0.998

Post-hoc Tukey-adjusted pairwise comparisons for D' between sessions using the linear model. Mean differences, standard errors (SE), t-values, and adjusted p-values are provided. No statistically significant differences were found between any session pairs ($p > 0.05$).

Figure 7. Evolution of D' Across Three Sessions Using the Linear Model



The figure presents the mean ± standard deviation for each session, illustrating a slight decrease in D' over time, but without statistically significant pairwise differences

3.2.2.2 Hyperbolic model

Table 10. D'Across Three Sessions Using the Hyperbolic Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
D' hyp 1	20	91.6 ± 14.2	58.7 - 114	6.35	0.004
D' hyp 2	20	83.9 ± 5.17	77.4 - 93.6		
D' hyp 3	20	83.9 ± 3.86	75.3 - 87.8		

Evolution of D' across three sessions using the hyperbolic model. Values are presented as mean ± standard deviation (SD) and minimum–maximum range. A significant session effect was observed ($F(2,38) = 6.35$, $p = 0.004$), suggesting a reduction in D' over time.

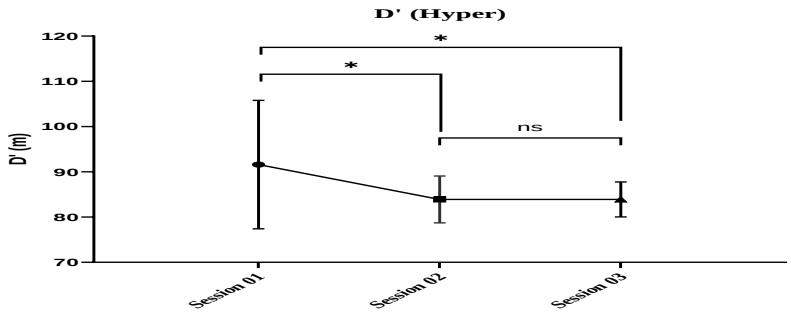
Table 11. Post-Hoc Pairwise Comparisons of D'Between Sessions Using the Hyperbolic Model

post hoc

Comparison						
Session		Session	Mean difference	Standard error	t	ptukey
S01	-	S02	7.6530	2.89	2.6494	0.040
	-	S03	7.7285	2.98	2.5897	0.045
S02	-	S03	0.0755	1.17	0.0645	0.998

Significant reductions in D' were observed between Session 1 and Session 2, and between Session 1 and Session 3 ($p < 0.05$), while no significant difference was found between Session 2 and Session 3 ($p > 0.05$).

Figure 8. Evolution of D' Across Three Sessions Using the Hyperbolic Model



The figure presents mean ± standard deviation, illustrating a significant drop in D' after Session 1, with stability thereafter.

3.2.2.3 1/time model

Table 12. D'Across Three Sessions Using the 1/Time Model

	N	Mean ± SD (m)	Min - Max	F	P-Value
D' 1/temps 1	20	88.6 ± 11.6	56.4 - 108	4.91	0.013
D' 1/temps 2	20	82.6 ± 3.68	76.9 - 91.7		
D' 1/temps 3	20	82.6 ± 4.38	75.7 - 87.3		

Evolution of D' across three sessions using the 1/Time model. Values are presented as mean ± standard deviation (SD) and minimum–maximum range. A significant session effect was observed ($F(2,38) = 4.91$, $p = 0.013$), suggesting a reduction in D' over time.

Table 13. Post-Hoc Pairwise Comparisons of D'Between Sessions Using the 1/Time Model

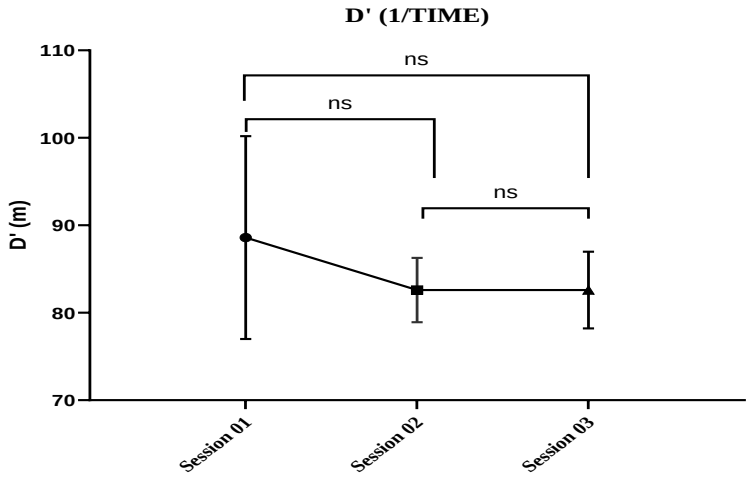
Post hoc

Comparison

Session		Session	Mean difference	Standard error	t	p-tukey
S01	-	S02	6.0295	2.603	2.3162	0.078
	-	S03	5.9925	2.679	2.2370	0.090
S02	-	S03	-0.0370	0.879	-0.0421	0.999

Post-hoc Tukey-adjusted pairwise comparisons for D' between sessions using the 1/Time model. Mean differences, standard errors (SE), t-values, and adjusted p-values are provided. No statistically significant differences were found between any session pairs ($p > 0.05$).

Figure 9. Evolution of D' Across Three Sessions Using the 1/Time Model



The figure presents mean ± standard deviation for each session, showing a trend towards a decrease in D', but without significant pairwise differences.

Discussion

The data from this study suggest that there are no statistically significant differences in values obtained using the linear, hyperbolic and 1/time models to estimate CS. The mean values were similar (maximum difference 0.01 m/s) and the standard deviations were not different, similarly to ANOVA results ($F = 0.527$, $p = 0.592$). These data are in agreement with those of Ruiz-Alias et al (2023), who observed a high degree of agreement among different critical power (CP) estimation models in trained athletes. Similarly, Clark & Macdermid (2021), in their study of elite road cyclists, found only minor differences between models, although they noted that accuracy might vary across disciplines.

For D′ the models had no statistically significant difference regarding D′ ($F = 2.29$, $p = 0.106$), the hyperbolic model yielded higher values (mean D′ = 86 m vs. 84.6 m for the 1/time model) though. The p value tends toward the threshold 0.05, indicating that either with a bigger sample size or a more sensitive experimental protocol, minor differences will likely show up. This is consistent with the study conducted by Drake et al (2024), who challenged the general applicability of the hyperbolic model, and proposed power-law-based alternatives which would improve representation of fatigue and pacing dynamics.

These findings suggest that under controlled experimental conditions and in a young athletic population, the three models can be used interchangeably to estimate CS and D′. However, for individualized training prescription or performance profiling, even small differences may carry practical significance.

The 3-session longitudinal analysis showed a significant linearly rising trend of critical speed in 3 models (all $p < 0.001$). Post hoc comparisons revealed significant differences between all session pairs, indicated that aerobic capacity would be increased over time, possibly because of exercise-induced training effects or physical adaptations. This gain is as well consistent with a slight increasing of the VO_2max from the first to the third session (50.7–52.9 ml/kg/min).

These findings align with those of Galbraith, Hopker, Cardinale, et al (2014), who reported positive CS changes in endurance runners over one year of structured training. Similarly, Barroso et al (2022), observed progressive CS

variation in an elite female swimmer, linked to training cycles and competition schedules.

The declining trend of D′ was in the hyperbolic model, with significant decrement between Session 1 and 2, and between Session 1 and 3 ($p < 0.05$). Both the linear and 1/time models were characterized by similar patterns, although they were not statistically significant. This attenuation in high-intensity workload capacity is likely indicative of a decrease in this sport specific component, potentially as a result of enhanced aerobic specific adaptations or accumulated fatigue.

These results partially echo the findings of Kordi et al (2019), who noted moderate fluctuations in D′ over a 12-month period, with greater instability compared to CS. They interpreted this variability as a reflection of D′'s sensitivity to external factors (e.g., glycogen availability, recovery) and internal conditions .

The progressive increase in CS evidences the claim that CS is a reliable and robust determinant of aerobic endurance, and also a valid index of performance trend in time. In contrast, D′ seems to be more variable and possibly influenced by short term influences, and should be interpreted with caution. These results also re-emphasize the role of CS as a fundamental variable in endurance training prescription (Jones et al., 2010), while D′ needs to be considered as an additional, albeit less robust parameter.

Conclusion

This study aimed to examine changes in **Critical Speed (CS)** and **work capacity above CS (D′)** in football players using three mathematical models: **hyperbolic, linear, and 1/time**, across three test sessions. It also explored performance trends and practical implications for athlete development. **CS showed consistent improvement** across sessions and varied slightly depending on the model used. The **linear and 1/time models** provided a better fit and more accurate reflection of player performance, particularly in realistic field settings. These improvements likely result from enhanced aerobic capacity and increased tolerance to sustained exertion, reinforcing CS as a reliable measure of endurance and resilience in football. In contrast, **D′ did not show significant differences across models**, though variations within sessions were observed. The relative stability of D′ may be due to individual differences in energy reserves and maximum effort capacity. However, the current short-

duration test protocols (3–12 minutes) may not fully capture the nuances of D′, suggesting that this variable is more complex and less easily assessed than CS. **Practical applications** of the findings emphasize the value of CS in guiding training loads and designing performance-based sessions. While D′ remains harder to evaluate precisely, it still provides insight into a player's ability to sustain high-intensity bursts beyond CS—a crucial aspect of football performance. Methodologically, the study supports using multiple models to assess performance, with the **linear and 1/time models** being especially practical for field use due to their simplicity and effectiveness. Expanding test durations and approaches could help refine the assessment of D′. In conclusion, the study underscores the importance of monitoring both CS and D′ in football. While CS offers clear benefits for tracking endurance and guiding training, further work is needed to improve the reliability and interpretation of D′. These findings contribute to a deeper understanding of player development and offer direction for future research in sports performance analysis.

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