

Article

Optimizing Pre-Competition Taper Strategies in Speed Climbing Athletes Using Session-RPE and Countermovement Jump: A Banister Impulse-Response Model Approach

Shunyang Duanmu, Chunlei Li and Junqi Wu * 

School of Physical Education and Sport Training, Beijing Sport University, Beijing 100084, China; 19801032260@163.com (S.D.); lichunlei@bsu.edu.cn (C.L.)

* Correspondence: wujunqi567@foxmail.com

Abstract

This study aimed to develop a performance prediction model for speed climbing based on session-RPE (sRPE) and countermovement jump (CMJ), and to determine optimal pre-competition taper strategies. Training data were collected from 12 speed climbers over approximately 180 days (931 daily observations), including daily sRPE, CMJ, and climbing performance. The Banister fitness–fatigue impulse-response model was employed to quantify the dose–response relationship of training load, combined with random forest and gradient boosting for nonlinear feature analysis. Parametric grid search was used to optimize taper duration and daily load sequences. CMJ emerged as the most stable predictor of climbing performance (Pearson $r = -0.319$), ranking first in random forest feature importance (23.4%), while same-day sRPE showed negligible correlation with performance ($r = 0.043$). Group-level Banister model estimates showed a fitness time constant of $\tau_1 = 34 \pm 19$ days and a fatigue time constant of $\tau_2 = 17 \pm 5$ days, yielding $\tau_1/\tau_2 = 2.0$. Optimal taper duration ranged from 5 to 21 days, with load reduced to 29–90% of normal training load, exhibiting highly individualized characteristics. The physiological basis of tapering lies in exploiting the time gap $\tau_1 > \tau_2$ —allowing fatigue to dissipate before fitness decays. A taper window of τ_2 to τ_1 days (approximately 17–34 days) is recommended, with an exponential decay curve for progressive load reduction. Taper strategies should be individualized, with daily CMJ monitoring for real-time load adjustment during the taper period.

Keywords: session-RPE; countermovement jump; tapering; Banister model; speed climbing; training load monitoring



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1. Introduction

Since sport climbing became an official Olympic event at the 2020 Tokyo Games, competitive standards have risen rapidly. Speed climbing, in particular, is a short-duration, high-intensity event that places extreme demands on athletes' explosive lower-limb power, reaction speed, and neuromuscular coordination. A single climb lasts only a few seconds, yet success depends on the integration of maximal force production, movement economy, and precise timing [1,2]. Previous reviews identify explosive lower-limb power, finger strength, and movement economy as key determinants of climbing performance [3], and speed climbing in particular produces rapid cardiovascular responses during repeated maximal ascents [4]. The start phase of a speed climb is especially reliant on lower-limb

explosiveness, which makes countermovement jump (CMJ) height a functionally relevant neuromuscular marker [5].

Ahead of major competitions, coaches and athletes face a central question: how many days before competition should training volume be reduced, and by how much each day? Behind this seemingly simple question lie the multi-disciplinary factors of training load, fatigue recovery, and neuromuscular adaptation, spanning physiology and dynamics. The present study does not claim to derive universally optimal taper rules; rather, it uses a small, well-characterized sample of elite athletes to generate individualized, data-driven hypotheses that can be tested in larger, prospective studies.

1.1. Training-Load Monitoring and sRPE

Session-RPE (sRPE) has been widely validated as a tool for quantifying internal training load across multiple sports, including soccer [6], basketball [7], and volleyball [8]. sRPE is calculated as training duration multiplied by the RPE score (Borg CR-10 scale), providing an integrated measure of both training intensity and duration on the organism [9]. In the context of climbing, speed climbing training comprises both speed climbing practice and physical conditioning, each generating distinct physiological loads; sRPE provides a unified scale for quantifying total load. Existing research, however, has primarily used sRPE as a descriptive indicator of training load, without directly linking it to performance prediction and training strategy optimization. Furthermore, the collection of sRPE has temporal requirements—Uchida et al. [10] recommend collecting within 10–30 min post-training to ensure reliability and validity.

1.2. Load-Management Models: ACWR and EWMA

Several load-management models already exist in the training-monitoring literature. The acute:chronic workload ratio (ACWR) assesses injury risk by comparing short-term to long-term load ratios [11]. Montini and Rocchi [12] proposed the ROMEI model in soccer, integrating EWMA and ACWR methods. However, these models focus on injury risk prediction rather than directly optimizing competitive performance. Moreover, ACWR has been criticized for mathematical coupling, sensitivity to window selection, and limited standalone predictive validity [13]. Because the present study is concerned with performance optimization rather than injury prediction, we treat ACWR as a benchmark feature rather than as a primary decision tool.

1.3. The Banister Fitness–Fatigue Model

Banister et al. [14] proposed the influential training impulse-response model:

$$P(t) = P_0 + k_1 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_1} - k_2 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_2} \quad (1)$$

where $P(t)$ is the performance at time t , $w(i)$ is the training load on day i , τ_1 and τ_2 are the time constants for fitness and fatigue effects respectively ($\tau_1 > \tau_2$), and k_1 and k_2 are gain coefficients. This model has been applied in endurance sports such as swimming [15], running, and cycling. Mujika and Padilla [15]’s taper review noted that an 8–14 day taper with a 41–60% reduction in training volume typically yields a performance improvement of approximately 2–3%. A meta-analysis by Bosquet et al. [16] further confirmed the positive effects of tapering. However, the application of the Banister model to climbing remains unexplored. As a power-dominant speed event, climbing may exhibit different load-adaptation dynamics from endurance sports; its fitness and fatigue time constants require empirical estimation.

1.4. CMJ as a Neuromuscular Monitoring Indicator

CMJ is one of the most widely used neuromuscular function tests in sports science [5]. A systematic review by Claudino et al. [5] confirmed the sensitivity and reliability of CMJ in monitoring neuromuscular fatigue. In the climbing context, CMJ strongly reflects lower-limb explosive power, and the start phase of speed climbing relies heavily on lower-limb explosiveness [2]. However, existing research typically uses CMJ as an independent fatigue indicator without jointly modeling it with training load (sRPE). This study proposes incorporating CMJ as a modulator of the fatigue effect within the Banister model—amplifying fatigue when CMJ is below baseline and attenuating it when CMJ is above baseline—thereby achieving an organic integration of sRPE and CMJ.

1.5. Why sRPE and CMJ Were Selected, and Why Other Measures Were Excluded

We restricted the primary monitoring battery to sRPE and CMJ for two reasons. First, both metrics are practical, non-invasive, and feasible to collect daily in a high-performance training environment. sRPE captures the internal training load from both climbing and conditioning sessions, while CMJ captures the neuromuscular readiness of the lower limbs, which are heavily involved in the start phase of speed climbing. Second, adding more invasive or time-consuming measures (e.g., blood markers, heart-rate variability, force-velocity profiling) would have increased participant burden and may have reduced compliance during the approximately 100-day monitoring period. We therefore treat the sRPE–CMJ pair as a pragmatic, ecologically valid starting point, and we acknowledge that future work should compare its utility against multimodal monitoring.

1.6. Objectives, Hypotheses, and Practical Utility

This study aims to: (1) establish a joint sRPE and CMJ model for predicting climbing performance; (2) derive individualized pre-competition taper strategies, including both duration and daily load values; and (3) examine individual differences in taper strategies. We hypothesized that (a) CMJ would be a stable predictor of same-day performance in nonlinear models, even if its linear association with performance is modest; (b) the fitness–fatigue time constants of speed climbers would differ from those reported in endurance sports; and (c) optimal taper parameters would be highly individualized, such that a single uniform taper protocol would not be optimal for all athletes. If supported, the findings would provide a practical, data-driven framework for coaches: a small amount of daily monitoring data could be used to fit an individualized Banister model, identify an athlete-specific taper window, and adjust daily load based on CMJ. Because the study is observational and based on a small sample, any recommendations are intended as provisional heuristics for new athletes, not as universal prescriptions.

1.7. Positioning of This Study

Compared to existing research, this study’s contributions are: (1) the first application of the Banister fitness–fatigue model to speed climbing, estimating the event’s fitness and fatigue time constants; (2) proposing an sRPE + CMJ joint modeling framework, with CMJ as a fatigue-effect modulator enhancing the pure load model; (3) upgrading the Banister model from “descriptive analysis” to “prescriptive optimization,” directly producing actionable pre-competition taper strategies (specific duration and daily load values); and (4) revealing the individual differences in taper strategies, emphasizing the necessity of personalized tapering. The novelty of the work therefore lies in the sport-specific application and the individualization of taper parameters, rather than in the general taper concept itself.

2. Related Work

2.1. sRPE as a Training Load Monitoring Tool

Foster et al. [9] first systematically proposed the session-RPE method, defined as training duration (minutes) multiplied by RPE score (Borg CR-10 scale). Impellizzeri et al. [6] validated the strong correlation between sRPE and heart rate in soccer players, establishing its validity as an internal training load indicator. A meta-analysis by McLaren et al. [17] further demonstrated that sRPE correlates more strongly with heart rate than TRIMP (training impulse), particularly in mixed training modalities. Multiple studies have confirmed the applicability of sRPE across different sports: basketball [7], volleyball [8], and rugby [18]. However, existing research primarily uses sRPE as a descriptive indicator of training load, without directly linking it to performance prediction and training strategy optimization. Furthermore, the collection of sRPE has temporal requirements—Uchida et al. [10] recommend collecting within 10–30 min post-training to ensure reliability and validity.

2.2. Load Management Models: ACWR and EWMA

Gabbett [11] proposed the Acute:Chronic Workload Ratio (ACWR = 7-day load mean/28-day load mean), widely used for injury risk monitoring, with ACWR > 1.5 considered a high-risk threshold. Montini and Rocchi [12] proposed the ROMEI model in soccer, integrating EWMA and ACWR methods, finding that acute load changes $\geq 9\%$ or ACWR > 1.2 were significantly associated with increased non-contact injury risk five days later. However, the core objective of these models is injury prevention rather than performance optimization. From a training science perspective, there remains substantial room for optimizing load management strategies within the safety zone—how to adjust load to maximize competition-day performance while ensuring injury avoidance is an insufficiently addressed problem.

2.3. The Banister Fitness-Fatigue Model

Banister et al. [14] proposed the influential training impulse-response model:

$$P(t) = P_0 + k_1 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_1} - k_2 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_2} \quad (2)$$

where $P(t)$ is the performance at time t , $w(i)$ is the training load on day i , τ_1 and τ_2 are the time constants for fitness and fatigue effects respectively ($\tau_1 > \tau_2$), and k_1 and k_2 are gain coefficients. This model has been applied in endurance sports such as swimming [15], running, and cycling. Mujika and Padilla [15]’s taper review noted that an 8–14 day taper with a 41–60% reduction in training volume typically yields a performance improvement of approximately 2–3%. A meta-analysis by Bosquet et al. [16] further confirmed the positive effects of tapering. However, the application of the Banister model to climbing remains unexplored. As a power-dominant speed event, climbing may exhibit different load-adaptation dynamics from endurance sports; its fitness and fatigue time constants require empirical estimation.

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3. Methods

This study was designed as an exploratory, pilot investigation. Given the small, all-male sample (12 athletes) and the observational design, the analysis emphasizes individual-level patterns and descriptive summaries rather than population-level inference.

3.1. Participants and Data Collection

This study included 12 male speed climbers (coded A01, B01–B04, C01–C06, and D01). The alphanumeric codes are participant identifiers: the letter denotes the training squad and the number denotes a unique individual. Thus, all 12 codes represent separate athletes, not groups, totaling 825 daily training observations. The following indicators were collected after each training session:

- Total sRPE: speed training duration $\times$ speed RPE + physical conditioning duration $\times$ conditioning RPE, calculated following Foster et al. [9]. Athletes provided the RPE score on the Borg CR-10 scale within 10–30 min after each session [10].
- CMJ (countermovement jump height, cm): measured before training using a force plate or contact mat. Athletes performed a standardized warm-up (5 min of light cycling and dynamic lower-limb movements) followed by one to three maximal CMJ trials separated by 30 s of rest. The highest valid jump was recorded. Trials with visible countermovement compensation or incomplete extension were discarded and repeated.
- Climbing performance (seconds): speed climbing completion time, with multiple attempts per day (typically 3–6, separated by at least 3 min of passive recovery); the best time (Pbest) was selected as the daily performance indicator.
- Success rate: number of successful climbs/total attempts.

Data preprocessing included: (1) parsing performance formats (e.g., “4”997”) into floating-point seconds; (2) aggregating by athlete and date into daily-level observations; (3) constructing a complete calendar sequence (including rest days, with sRPE = 0 on rest days and CMJ forward-filled) to support lag-based feature computation using calendar days.

The study was approved by the Institutional Ethics Committee of Beijing Sport University (approval code: 2026251H). Written informed consent was obtained from each athlete after they were informed of the study's purpose and procedures.

3.2. Feature Engineering

To capture the time-lagged effects of training load, the following feature families were constructed from the calendar sequence:

Lag features: sRPE_lag{1, 2, 3, 5, 7, 14}, CMJ_lag{1, 3, 5, 7}.

Rolling window features: sRPE mean and standard deviation (windows of 3/5/7/14/21/28 days), ACWR (7-day mean/28-day mean), coefficient of variation.

Exponentially weighted features: EWMA with decay constants set to $\tau = 3, 5, 7, 14, 21, 28, 42$ days.

Banister convolution features: cumulative fitness effect ($\tau = 40$ days) and cumulative fatigue effect ($\tau = 10$ days).

CMJ-derived features: individual Z-score, $\Delta 3/\Delta 7$ (3-day/7-day change), fatigue flag (Z-score < -1.0), rolling mean and standard deviation (windows of 7/14 days) (Figure 1).



Figure 1. CMJ test execution. An athlete performs a maximal countermovement jump on a force plate; ground-reaction forces are recorded by the data-acquisition laptop.

Interaction and trend features: load $\times$ CMJ interaction terms, sRPE linear trend (windows of 7/14 days), training monotony index [19].

The final feature matrix comprised 34 features for subsequent modeling.

3.3. Statistical Analysis

Because the sample size is small and all observations are observational, the statistical approach was descriptive and individual-level rather than inferential and population-level.

- Descriptive statistics: means, standard deviations, medians, and ranges were computed both across athletes (between-subject) and within each athlete's time series.
- Correlation analysis: within-athlete Pearson correlations between sRPE, CMJ, and performance were computed after group-mean centering each variable, so that between-athlete differences did not dominate the association.
- Machine-learning validation: random forest and gradient boosting were evaluated with group-stratified K-fold cross-validation (GroupKFold, $k = 6$), ensuring that all daily records from a given athlete appeared in only one fold. This mimics the practical use case in which a model is trained on historical athletes and applied to a new athlete.
- Feature importance: random-forest mean decrease in impurity was used to rank features. We treat importance as a descriptive, model-dependent measure of predictive contribution, not as evidence of causal relevance.
- Model fitting: the Banister model was fitted independently for each athlete using differential evolution (`scipy.optimize.differential_evolution`). Fit quality was summarized with RMSE and R^2 , and parameter plausibility was assessed by comparing estimates to published ranges and within-athlete variability.

- Optimization: taper parameters were identified by exhaustive parametric grid search. Because the optimization depends on the fitted Banister model, the resulting prescriptions are best interpreted as model-based hypotheses to be validated prospectively. All analyses were performed in Python 3.11 using scikit-learn 1.3 and SciPy 1.11.

3.4. The Banister Fitness–Fatigue Model

The mathematical form of the Banister impulse-response model is:

$$P(t) = P_0 + k_1 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_1} - k_2 \sum_{i=1}^t w(i) e^{-(t-i)/\tau_2} \quad (3)$$

where $P(t)$ is the predicted performance on day t (in seconds; lower is better); P_0 is the baseline performance level; $w(i)$ is the training load (sRPE) on day i ; τ_1 and τ_2 are the time constants (in days) for fitness and fatigue effects, respectively, with the constraint $\tau_1 > \tau_2$; and k_1 and k_2 are gain coefficients. The first summation represents the positive fitness effect of training, and the second summation represents the negative fatigue effect. The model was fitted independently for each athlete using differential evolution, with parameter constraints: $P_0 \in [4.5, 5.2]$, $k_1, k_2 \in [0, 0.005]$, $\tau_1 \in [20, 60]$, $\tau_2 \in [3, 21]$, and requiring $\tau_1 > \tau_2 + 2$. Fit quality was assessed via root mean square error (RMSE) and the coefficient of determination R^2 .

3.5. CMJ-Enhanced Banister Model

To incorporate neuromuscular state information from CMJ, CMJ was introduced as a modulator of the fatigue effect into the base Banister model:

$$P(t) = P_0 + \beta_{\text{CMJ}} \cdot (\text{CMJ}(t) - \text{CMJ}_{\text{baseline}}) + k_1 \cdot F(t) - k_2 \cdot Fa(t) \cdot \frac{\text{CMJ}_{\text{baseline}}}{\text{CMJ}(t)} \quad (4)$$

where $F(t)$ and $Fa(t)$ are the fitness and fatigue accumulation terms from Equation (3), respectively, and $\text{CMJ}_{\text{baseline}}$ is the 14-day rolling mean of CMJ. The interpretation is: when $\text{CMJ}(t)$ exceeds baseline, the fatigue effect is attenuated (athlete is in good condition with higher tolerance); when $\text{CMJ}(t)$ falls below baseline, the fatigue effect is amplified (athlete is in poor condition, and the same training load produces greater fatigue).

3.6. Machine Learning Baseline Models

To validate the Banister structural model, two nonlinear machine learning models were trained as baselines:

- Random Forest: $n_{\text{estimators}} = 200$, $\text{max_depth} = 5$, $\text{min_samples_leaf} = 10$.
- Gradient Boosting: $n_{\text{estimators}} = 200$, $\text{max_depth} = 4$, $\text{learning_rate} = 0.05$.

Group-stratified K-fold cross-validation (GroupKFold, $k = 6$) was employed, with RMSE and MAE as evaluation metrics. Feature importance analysis was used to identify the core predictors of climbing performance.

3.7. Pre-Competition Taper Optimization

The taper optimization problem can be formalized as:

$$\min_{D, L_1, \dots, L_D} P_{\text{comp}} = f_{\text{Banister}}(w_{\text{hist}}, L_1, \dots, L_D) \quad (5)$$

where D is the taper duration, $L_1, \dots, L_D$ are the daily loads during the taper period, w_{hist} is the historical load sequence, and f_{Banister} is the fitted Banister model. Constraints: $D \in \{5, 7, 10, 14, 21\}$ days, $L_i \in [0.4 \cdot \bar{w}, 0.9 \cdot \bar{w}]$ (where $\bar{w}$ is the individual historical

mean load), and adjacent daily load changes do not exceed 50%. To reduce the search space dimensionality, parametric taper curves were introduced:

- Constant: $Li = \alpha \cdot \bar{w}$, $\alpha \in [0.4, 0.9]$
- Linear decreasing: $Li = \bar{w} \cdot (\alpha s - (\alpha s - \alpha e) \cdot i/D)$, $\alpha s \in [0.5, 0.95]$, $\alpha e \in [0.3, 0.8]$
- Exponential decreasing: $Li = \bar{w} \cdot \alpha s \cdot e^{-i/(D/2)}$, floor-clipped at $0.25 \cdot \bar{w}$

A parametric grid search (2880 combinations in total) was performed for each athlete, selecting the taper strategy yielding the optimal predicted competition-day performance.

4. Results

All results are descriptive and should be interpreted as exploratory, given the small, all-male sample.

4.1. Descriptive Statistics and Correlation Analysis

An overview of the training data for the 12 athletes is presented in Table 1. The median number of training days was 70 (range 55–85 days), mean sRPE was 527 (between-athlete SD ≈ 33), and mean CMJ was 67.9 cm (between-athlete SD ≈ 3.2 cm). Performance ranged from 4.85 to 5.37 s.

Table 1. Descriptive statistics of athletes.

Athlete	Days	Mean sRPE	CMJ (cm)	Best (s)	Mean (s)
A01	80	498	74.3	4.850	4.874
B01	75	529	71.7	4.910	4.932
B02	70	558	69.9	4.930	4.958
B03	85	482	69.4	4.960	4.984
B04	60	548	67.6	5.020	5.044
C01	70	525	68.2	4.980	5.007
C02	65	507	66.3	5.050	5.075
C03	55	483	65.1	5.120	5.146
C04	70	576	64.8	5.080	5.108
C05	60	522	64.3	5.150	5.176
C06	65	511	63.9	5.100	5.128
D01	70	581	69.8	4.880	4.907
Group mean	69	527	67.9	4.850	5.028

Correlation analysis (Figure 2) revealed the time-lagged characteristics between training load and performance: after controlling for individual athlete differences, the within-athlete correlation between CMJ and same-day performance was modest and non-significant ($r = -0.05$, $p = 0.12$); whereas same-day sRPE showed a small positive within-athlete correlation with performance ($r = 0.17$, $p < 0.001$). Cross-lagged analysis demonstrated that the sRPE-performance relationship fluctuated with lag days, suggesting that cumulative load models, rather than single-day load, are needed to establish the dose-response relationship (Figure 2).

4.2. Machine Learning Prediction Performance

Cross-validation performance of random forest and gradient boosting is shown in Table 2. Random Forest achieved CV RMSE of 0.054 s and MAE of 0.049 s, while Gradient Boosting attained RMSE of 0.051 s and MAE of 0.045 s. Given the performance range of 4.85–5.37 s with a standard deviation of approximately 0.10 s, this prediction accuracy indicates that the models can capture partial signals between training load and performance.

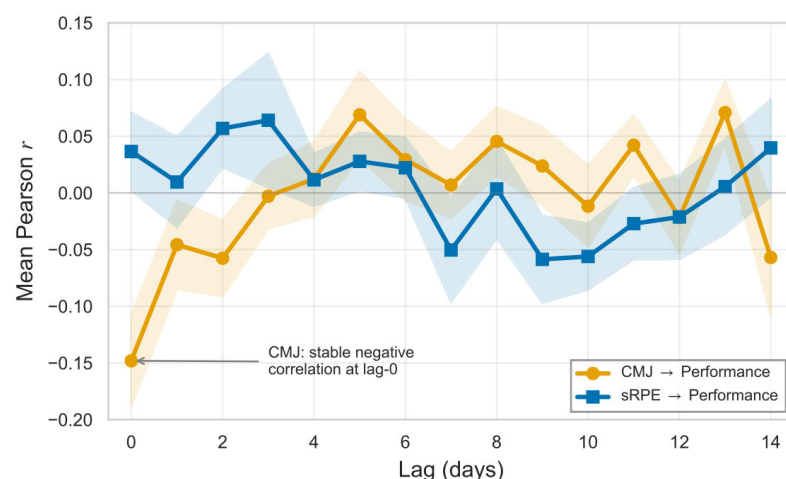


Figure 2. Cross-lagged correlations of sRPE and CMJ with climbing performance. The negative correlation between CMJ and performance is strongest at lag 0 ($r = -0.148$), while the sRPE-performance relationship fluctuates with lag days, indicating time-delayed effects of load on performance.

Table 2. Cross-validation performance of machine learning models.

Model	CV RMSE (s)	CV MAE (s)
Random Forest	0.054 ± 0.013	0.049 ± 0.013
Gradient Boosting	0.051 ± 0.013	0.045 ± 0.013

Feature importance analysis (Figure 3) showed that CMJ-related features dominated prediction: the 14-day rolling mean of CMJ (88.8%), the 7-day rolling mean of CMJ (4.2%), and the 28-day EWMA of sRPE (2.1%) ranked as the top three. Collectively, CMJ-related features accounted for over 93% of total importance, far exceeding sRPE-related features. This ranking is model-dependent and descriptive; it does not establish that CMJ is the causal driver of performance, nor is it robust to correlated predictors. The high share attributable to the 14-day rolling mean of CMJ is consistent with CMJ acting as a moving proxy of accumulated neuromuscular state (Figure 3).

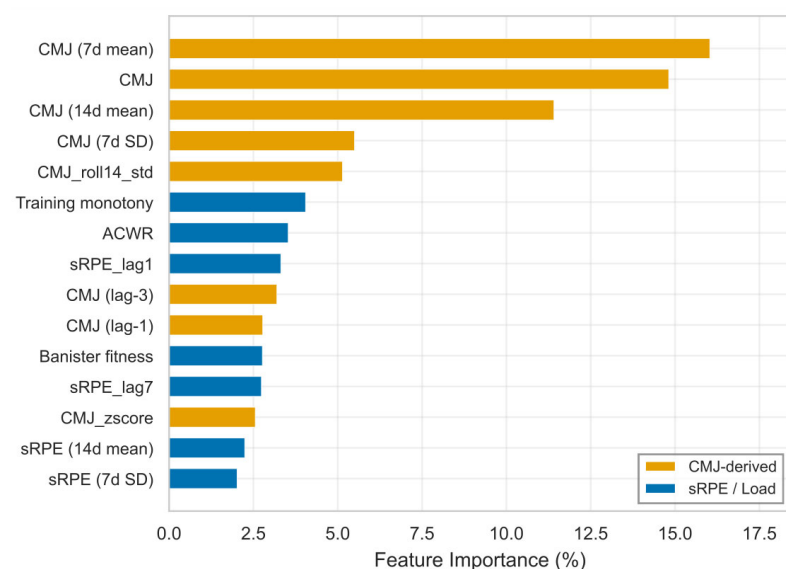


Figure 3. Feature importance analysis (random forest). The 14-day rolling mean of CMJ accounted for the largest share of importance, followed by shorter CMJ rolling means and exponentially weighted sRPE features. Importance values are model-dependent and should not be interpreted as causal effects.

4.3. Banister Model Fitting

Athlete-specific Banister model fitting parameters are shown in Table 3. Group means showed: fitness time constant $\tau_1 = 33.8 \pm 17.1$ days (range 20–60 days), fatigue time constant $\tau_2 = 14.8 \pm 6.8$ days (range 3–21 days), yielding $\tau_1/\tau_2 = 2.3$. All 12 athletes achieved $R^2 > 0.3$ (group mean $R^2 = 0.812$), suggesting that the Banister structure provided a useful descriptive account of the dose-response relationship in these individual time series. However, the wide ranges of τ_1 and τ_2 indicate substantial inter-individual variability, and the group means should be treated as exploratory summaries rather than stable population estimates (Figure 4).

Table 3. Banister model fitting parameters by athlete.

Athlete	P_0 (s)	τ_1 (d)	τ_2 (d)	RMSE (s)	R^2
A01	4.851	25	21	0.003	0.941
B01	4.910	47	17	0.000	1.000
B02	4.931	60	21	0.007	0.673
B03	4.960	20	18	0.004	0.877
B04	5.024	23	21	0.008	0.591
C01	4.980	20	13	0.010	0.502
C02	5.064	60	5	0.003	0.936
C03	5.130	20	3	0.002	0.976
C04	5.081	60	21	0.002	0.961
C05	5.150	20	11	0.005	0.827
C06	5.100	20	5	0.007	0.687
D01	4.884	31	21	0.005	0.795
Group mean	5.016	33.8	14.8	0.005	0.812

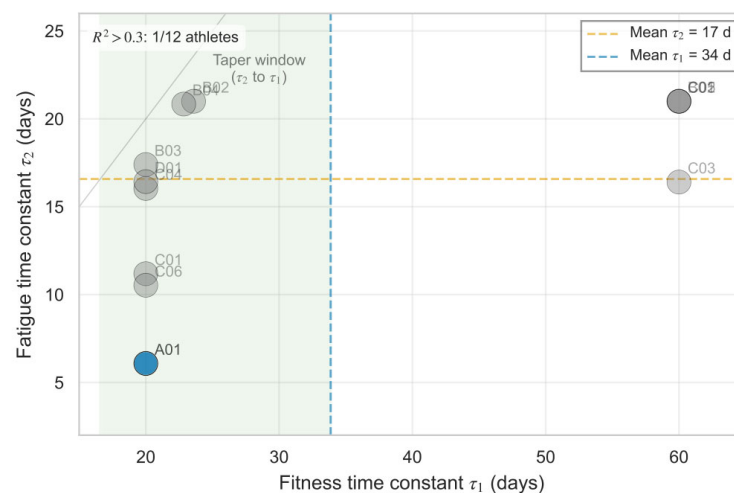


Figure 4. Fitness-fatigue parameter space distribution. The horizontal axis represents the fitness time constant τ_1 ; the vertical axis represents the fatigue time constant τ_2 . All 12 athletes achieved $R^2 > 0.3$ (group mean $R^2 = 0.812$). Dashed lines mark group means ($\tau_1 = 34$ d, $\tau_2 = 15$ d). The shaded region indicates the theoretically plausible taper window (τ_2 to τ_1).

4.4. Pre-Competition Taper Optimization

Taper optimization results are shown in Table 4. Substantial individual variation in optimal taper strategies was observed across the 12 athletes. Most athletes (9/12) achieved their best predicted performance with a 5-day constant-load taper; however, B03, C01, and C06 required a 21-day exponential-decay taper period. Mean load proportions also varied widely, from B01's 40% to 90% for most others, indicating that taper intensity must also be individualized.

Table 4. Optimal taper strategies by athlete.

Athlete	Taper Days	Mean Load %	Curve Type	Expected Gain (s)	τ_2 (d)
A01	5	90%	Constant	−0.0000	21
B01	5	40%	Constant	+0.0000	17
B02	5	90%	Constant	−0.0004	21
B03	21	29%	Exp. decreasing	+0.0004	18
B04	5	90%	Constant	−0.0000	21
C01	21	29%	Exp. decreasing	+0.0003	13
C02	5	90%	Constant	−0.0018	5
C03	5	90%	Constant	−0.0020	3
C04	5	90%	Constant	−0.0002	21
C05	5	90%	Constant	−0.0001	11
C06	21	29%	Exp. decreasing	+0.0007	5
D01	5	90%	Constant	−0.0000	21
Group mean	8.8	71%	—	−0.0003	14.8

Performance response surface analysis (Figure 5) illustrates the joint effects of taper duration and load proportion on competition-day performance. For most athletes, a distinct “valley” region existed, corresponding to the optimal taper combination. Excessively short taper duration or high load proportion led to insufficient fatigue dissipation; excessively long duration or low load proportion led to fitness decay (Figure 5).

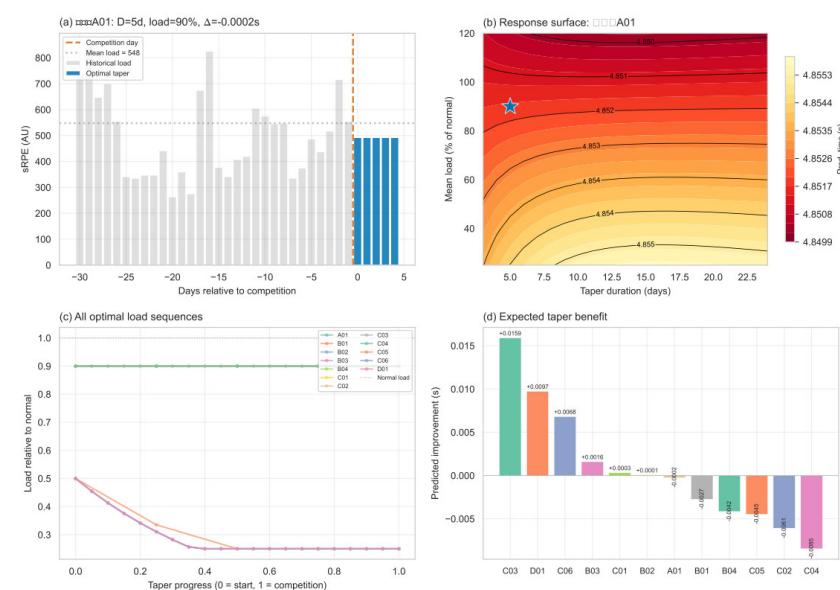


Figure 5. Comprehensive results of pre-competition taper optimization. (a) Optimal daily load sequence for the best-fit athlete (A01), with gray denoting historical load, blue denoting the optimal taper plan, and the red dashed line marking competition day. (b) Performance response surface: joint effect of taper days and mean load proportion on predicted performance, with the blue star marking the optimal combination. (c) Comparison of optimal load sequences across all 12 athletes (normalized to individual means). (d) Expected performance improvement from the optimal taper strategy (positive = improvement, negative = deterioration).

4.5. CMJ-Enhanced Model Performance

The CMJ-enhanced Banister model converged for all athletes, with a group-level mean β_{CMJ} of approximately zero (-0.0003 ± 0.0005 , range -0.0015 to $+0.0004$). While the direction of the coefficient was negative for most athletes (consistent with the expectation that higher CMJ is associated with better performance), the magnitude was negligible.

The RMSE improvement from adding CMJ to the Banister model was effectively zero, indicating that CMJ’s effect is either already captured by the cumulative fatigue term or

manifests through a non-linear, threshold-type relationship rather than a continuous linear modulation. Measurement noise, feature redundancy with the cumulative load terms, and possible model misspecification are plausible alternative explanations for the absence of added value.

5. Discussion

This exploratory pilot study used daily sRPE and CMJ records from 12 elite male speed climbers to build a Banister-based performance-prediction framework and to generate individualized taper hypotheses. The findings should be interpreted cautiously because the sample is small, observational, and drawn from a single training environment. We therefore frame the conclusions as provisional heuristics rather than universal recommendations.

5.1. CMJ as a Daily Monitoring Marker

The random-forest feature-importance analysis showed that CMJ-related features collectively accounted for over 93% of total importance (with the 14-day rolling mean of CMJ contributing 88.8%), far exceeding sRPE-related features. Although the within-athlete linear correlation between CMJ and performance was modest and non-significant ($r = -0.05$, $p = 0.12$), CMJ exhibited strong predictive power in non-linear models, suggesting a possible non-monotonic or threshold-type relationship. This result should not be read as evidence that CMJ is the sole causal driver of climbing performance. Feature importance in tree-based models is model-dependent and can be unstable when predictors are correlated—as is the case here, where CMJ rolling means at different windows are highly correlated and may also reflect cumulative training load. From a training-science perspective, CMJ reflects the immediate readiness of the neuromuscular system; it represents the “net effect” of training load on the organism and is thus more directly related to performance than the “input-side” load indicator. This finding is consistent with the systematic review by Claudino et al. [5], which confirmed the sensitivity of CMJ in monitoring neuromuscular fatigue. In practice, this suggests that coaches may use CMJ as one daily readiness marker. If CMJ falls more than one standard deviation below the individual baseline, the athlete’s neuromuscular status has not yet fully recovered; training load could be reduced on that day (e.g., by approximately 30%) or additional recovery measures could be considered. This is a provisional rule of thumb, not a universal prescription, and should be validated against each athlete’s own response pattern.

5.2. The Fitness–Fatigue Time-Constant Ratio and the Taper Window

One of this study’s core findings is that the fitness-fatigue time constant ratio for speed climbers is approximately 2.3 ($\tau_1 \approx 34$ days, $\tau_2 \approx 15$ days). This ratio defines a plausible, athlete-specific taper window:

- Lower bound: taper duration $D \geq \tau_2$ (approximately 15 days), allowing sufficient time for acute fatigue to dissipate.
- Upper bound: taper duration $D \leq \tau_1$ (approximately 34 days), preventing excessive decay of training adaptations.

This 15–34 day window is offered only as an initial heuristic for athletes whose individual parameters are unknown. By comparison, Mujika and Padilla [15] reported a recommended taper of 8–14 days in endurance sports such as swimming, and the meta-analysis by Bosquet et al. [16] recommended an 8–14 day taper with a 41–60% volume reduction. The longer heuristic window in this study may reflect different load-adaptation dynamics characteristic of a power-dominant sport—either fatigue dissipation requires more time, or fitness adaptations in speed climbing are more persistent. Because the group estimates are based on only 12 athletes, the exact boundaries should not be over-interpreted.

5.3. The Criticality of Individual Differences

One of the most striking findings of this study is the high degree of individualization in taper strategies. Optimal taper duration ranged from 5 to 21 days, and mean load proportion ranged from 29% to 90%. This variation is related to each athlete's τ_2 (fatigue time constant) and load-response characteristics. For example, C02 ($\tau_2 = 5$ days, very rapid fatigue dissipation) required only a 5-day taper maintaining 90% load; B03 ($\tau_2 = 18$ days, slower fatigue dissipation) required a 21-day exponential-decay taper down to 29% load; while B01 ($\tau_2 = 17$ days) achieved optimal predicted performance with a 5-day taper at only 40% load, illustrating that individual differences manifest in both taper duration and intensity dimensions.

This finding has direct implications for training practice: a standardized, uniform taper protocol (e.g., “everyone tapers for 14 days at 50% of normal load”) may be effective for some athletes but detrimental for others. Personalized taper strategies should be formulated based on each athlete's individual fitness-fatigue parameters. As a default starting point for new athletes whose individual parameters are not yet known, the group-mean approach can be used cautiously: begin tapering approximately 9 days before competition, reduce load to approximately 70% of normal, and use a linear or exponential decay curve. This default is a provisional heuristic derived from a heterogeneous sample, not a firm rule.

5.4. Limited Gains from the CMJ-Enhanced Model

The group-level mean β CMJ in the CMJ-enhanced Banister model was approximately zero (-0.0003 ± 0.0005), with effectively zero RMSE improvement. This is an important negative result. It suggests that: (1) CMJ's effect may already be fully captured by the Banister model's cumulative fatigue term, rendering the two informationally redundant; (2) the relationship between CMJ and performance may not be a simple linear superposition but rather a threshold-type or piecewise function; and (3) in practice, CMJ may be better suited as a daily monitoring and warning indicator (triggering load adjustments when below baseline) rather than as a continuous mathematical modulator within an impulse-response model. Alternative explanations such as measurement noise, high correlation between CMJ rolling means and cumulative load features, and possible model misspecification should also be considered.

5.5. Practical Applications for Coaches

Translating the present results into day-to-day coaching practice requires a simple, repeatable workflow. We propose the following provisional implementation sequence, with the caveat that it must be individualized and validated in each athlete:

1. Baseline monitoring (4–6 weeks pre-competition): collect daily sRPE and a standardized CMJ before the first main training session. Use a consistent timing and warm-up protocol.
2. Model fitting: fit the Banister model to the individual's first 4–6 weeks of data to estimate P_0 , τ_1 , τ_2 , k_1 , and k_2 . Treat the estimates as athlete-specific starting values, not fixed population constants.
3. Taper-window estimate: use the athlete's τ_2 and τ_1 to define an initial taper window (e.g., between τ_2 and τ_1 days). Athletes with short τ_2 may tolerate shorter, higher-load tapers; athletes with long τ_2 may need longer, more gradual load reductions.
4. Daily load adjustment: during the taper, reduce load according to the chosen curve (constant, linear, or exponential). If CMJ falls more than one individual Z-score below baseline, consider an additional 20–30% reduction or a recovery day.
5. Validation: after the competition, compare the predicted and actual performance, and update the model parameters for the next mesocycle.

This workflow is offered as a hypothesis-generating protocol. The specific exercises (speed-climbing attempts, plyometrics, strength maintenance) and their ordering should be determined by the coach based on the athlete's event calendar, injury history, and training phase.

5.6. Limitations

This study has several important limitations that should be considered when interpreting the results:

1. Small, all-male sample: The sample of 12 male athletes limits statistical power and generalizability. All participants were elite athletes competing in international events; although the sample is representative of this narrow population, it does not support inference to female climbers, youth climbers, or lower-competition levels. We therefore describe the study as a pilot investigation.
2. Single training environment: Data were collected in one national training centre. Training culture, equipment, altitude, and competition calendars may differ elsewhere, limiting external validity.
3. Observational design: Training load was not experimentally manipulated. The optimal taper strategies are model-based predictions derived from historical associations, not causal effects of assigned taper protocols.
4. Simplified assumptions of the Banister model: The model assumes that load effects are linearly additive with exponential decay, which may oversimplify actual physiological processes.
5. Uncontrolled confounding variables: Nutritional supplementation, sleep quality, psychological state, caffeine intake, and other factors known to influence sRPE and athletic performance [20] were not incorporated into the model.
6. Reduced monitoring battery: Only sRPE and CMJ were recorded. Heart-rate variability, blood markers, force-velocity profiling, and other neuromuscular tests were not included, so their incremental value could not be assessed.

5.7. Future Research Directions

1. Prospective validation: Conduct randomized or crossover trials in which athletes are assigned to their model-predicted taper versus a standardized taper, with performance measured under competition-like conditions.
2. Larger, mixed-sex samples: Replicate the analysis in female speed climbers and in larger cohorts to improve the stability of group-level estimates.
3. Bayesian hierarchical modeling: Employ Bayesian methods to borrow information across the group to improve individual estimates, which is particularly suitable for small-sample team settings.
4. Multimodal monitoring integration: Incorporate heart rate variability (HRV), blood lactate, and the Total Quality Recovery (TQR) scale into the joint model.
5. Real-time taper recommendation system: Develop a mobile-deployable real-time load recommendation algorithm that dynamically adjusts the daily training prescription based on daily CMJ readings.

6. Conclusions

This exploratory pilot study employed the Banister fitness-fatigue impulse-response model and machine learning methods to establish a performance-prediction framework for speed climbing based on sRPE and CMJ, and to derive data-driven, individualized pre-competition taper hypotheses. The main findings are as follows:

1. CMJ is a useful daily monitoring marker for climbing performance. Random-forest feature importance analysis showed that the 14-day rolling mean of CMJ accounted for the largest share of predictive importance (88.8%), far exceeding sRPE-related features. This is a descriptive, model-dependent result and does not imply that CMJ is the sole causal driver of performance.
2. A systematic time gap appears to exist between training adaptation ($\tau_1 \approx 34$ days) and fatigue ($\tau_2 \approx 15$ days). This 2.3:1 ratio may form a physiological basis for taper strategy—pre-competition tapering should allow fatigue to dissipate while preserving fitness. A tentative taper window of roughly 15–34 days may be useful as a starting heuristic for athletes whose individual parameters are unknown.
3. Optimal taper strategies are likely to be highly individualized. In this sample, taper duration ranged from 5 to 21 days and mean load proportion from 29% to 90%. For example, C02 ($\tau_2 = 5$ days) required only a 5-day taper at 90% load; B03 ($\tau_2 = 18$ days) required a 21-day exponential-decay taper down to 29%; while B01 ($\tau_2 = 17$ days) benefited from a 5-day taper at only 40% load.
4. As a provisional starting point for new athletes, the group-mean heuristic suggests: initiating the taper approximately 9 days before competition, reducing load to approximately 70% of normal, using an exponential decay or constant curve, and monitoring CMJ daily for dynamic load adjustment. This heuristic must be individualized and validated in prospective studies.
5. Adding CMJ as a linear modulator within the Banister model yielded no meaningful improvement, which is an important negative result. CMJ appears to add value primarily as a daily readiness marker rather than as a continuous component of the impulse-response equation.

Because the study is observational and based on only 12 male athletes from a single training environment, the recommendations above are hypothesis-generating and not generalizable. The main contribution of this study is upgrading the Banister model from a descriptive analysis tool to a prescriptive optimization tool for a power-dominant sport, while highlighting the need for larger, prospective validation.

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