

Effects of Squat Jumps versus Drop Jumps on Neuromuscular Fatigue in Women: Integrating Submaximal Testing and Complexity Analyses with Conventional Approaches

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Abstract

Purpose

We compared neuromuscular fatigue from plyometric (drop jump, DJ) versus concentric (squat jump, SJ) protocols to determine if submaximal variability and complexity analyses complement conventional maximal assessments.

Methods

Sixteen women performed 3×30 DJ or SJ on separate days. Pre/post-protocol assessments included perceived pain/exertion, countermovement jump (CMJ), maximal (MVIC) and 50% submaximal (SubMax50%) isometric contractions, and evoked torques. Analyses included EMG root mean square (RMS), torque coefficient of variation (CV), sample entropy, and multifractal detrended fluctuation analysis.

Results

Pain/exertion increased after both, especially DJ (interaction $p=.022$; DJ vs SJ $p=.044$). Significant interactions occurred for MVIC ($p=.046$), SubMax50% ($p=.007$), and CMJ ($p<.001$); values declined only after DJ ($p=.017-.020$). Single and doublet torques showed interactions ($p=.001-.008$), with greater impairments after DJ ($p=.002-.006$). Maximal M-wave (Mmax), voluntary activation, and MVIC EMG (RMS, RMS/Mmax, complexity) remained unchanged ($p=.19-.98$). During SubMax50%, interactions emerged for torque CV ($p=.003$) and entropy ($p=.040$), but not EMG entropy ($p=.10$); only DJ increased CV ($p<.001$) and reduced entropy ($p=.047$). SubMax50% RMS increased as a time effect ($p=.004$), while EMG multifractal PEAK showed an interaction ($p=.013$), decreasing after DJ ($p=.016$), and MAX showed a condition effect (DJ < SJ, $p=.006$); remaining measures were unchanged ($p=.07-.978$).

Conclusion

Stretch-shortening cycle exercise alters neuromuscular control strategies to compensate for peripheral fatigue, reducing force adaptability. Because conventional maximal assessments often mask these subtle neural adjustments, combining submaximal contractions with complexity analyses offers a more sensitive and ecologically valid approach for comprehensive fatigue monitoring in training and rehabilitation.

INTRODUCTION

Neuromuscular fatigue is a transient reduction in the capacity to generate force following prolonged or intense muscle activity (Allen et al. 2008; Gandevia 2001; Rampichini et al. 2020). Its development is

task-dependent and may reflect contributions from central processes, which impair the ability of the nervous system to voluntarily activate the muscle, and peripheral processes occurring at or distal to the neuromuscular junction, including impaired membrane excitability, metabolic disturbances, and excitation–contraction coupling failure (Allen et al. 2008; Hunter 2018). The relative contribution of these processes depends on the characteristics of the exercise performed (Babault et al. 2006). Identifying these contributions is important for understanding exercise-induced impairments and informing fatigue monitoring, recovery, and rehabilitation strategies.

Central and peripheral contributions to neuromuscular fatigue are commonly assessed using the signal amplitude during maximal voluntary isometric contractions (MVICs) combined with electrical stimulation and electromyography (EMG). These methods evaluate voluntary activation, muscle excitability, and contractile function across various exercise modalities (Babault et al. 2006; Cavalcante et al. 2022; De Oliveira et al. 2018; Drinkwater et al. 2009; Troiano et al. 2008). However, maximal tests may not fully capture force control impairments during the submaximal tasks typical of sports, occupational activities, and rehabilitation. Consequently, submaximal assessments evaluate the ability to maintain a prescribed force, frequently using the coefficient of variation (CV) of force or torque (DeAngelis et al. 1990; Hunter 2018; Pethick and Tallent 2022; Rampichini et al. 2020). For instance, force CV increases progressively during fatiguing tasks (Pethick et al. 2016) and detects age-related declines in force steadiness (Oomen and van Dieen 2017). Although CV quantifies the magnitude of force fluctuations, it does not describe their temporal organization and may consequently overlook changes in neuromuscular control.

Complexity-based analyses may complement conventional amplitude- and variability-based measures by quantifying the temporal structure of physiological signals (Pethick and Tallent 2022; Slifkin and Newell 1999), and are increasingly used in physiology and sport sciences (Babault et al. 2022; Babault et al. 2023; Babault et al. 2024; Ivanov et al. 1999; Lipsitz and Goldberger 1992; Lopes and Betrouni 2009; Stosic and Stosic 2006). Sample entropy (SampEn) quantifies signal regularity, whereas multifractal detrended fluctuation analysis (MFDFA) describes scale-dependent fluctuations and multifractal organization (Kantelhardt et al. 2002; Pincus 1991; West 2010). Under the loss-of-complexity framework, physiological systems exhibit structured variability across temporal scales; reduced organization may reflect a diminished capacity to adapt to physiological demands (Ivanov et al. 1999; Lipsitz and Goldberger 1992; Peng et al. 2009). While previous studies report altered neuromuscular signal complexity with fatigue, warm-up, and stretching (Babault et al. 2022; Hernandez and Camic 2019; Marri and Swaminathan 2016), these analyses have largely focused on isolated or single sustained contractions (Hernandez and Camic 2019; Talebinejad et al. 2010; Webber et al. 1995). Their ability to characterize fatigue following various locomotor tasks, such as those using different contraction modes, therefore remains insufficiently understood (Pethick and Tallent 2022).

Indeed, contraction mode is an important determinant of neuromuscular fatigue. For example, isometric and concentric exercises may similarly reduce maximal force despite differing central and peripheral contributions, with greater central fatigue following isometric exercise and greater peripheral fatigue following concentric exercise (Babault et al. 2006). Stretch-shortening cycle (SSC) activities also differ

from concentric-dominant tasks, as their eccentric component imposes substantial mechanical stress, potentially producing more pronounced exercise-induced muscle damage and delayed-onset muscle soreness (DOMS) (Arazi et al. 2016; Jamurtas et al. 2000). Accordingly, drop jumps (DJ, involving rapid eccentric-to-concentric transitions) and squat jumps (SJ, predominantly concentric) provide a relevant model for comparing task-dependent fatigue. However, whether submaximal contractions combined with variability- and complexity-based analyses can distinguish the neuromuscular fatigue profiles induced by these jumping modalities remains unclear.

To our knowledge, no study has integrated conventional neuromuscular assessments with variability and complexity-based analyses of maximal and submaximal contractions to compare fatigue following different jumping modalities. Therefore, this study compared the neuromuscular fatigue profiles induced by plyometric DJ and concentric-dominant SJ protocols in physically active women. We examined whether submaximal contractions combined with variability and complexity-based analyses provide complementary information beyond conventional maximal assessments. We hypothesized that DJ would induce greater peripheral fatigue and performance impairment than SJ. We further hypothesized that variability- and complexity-based measures obtained during submaximal contractions would detect fatigue-related alterations not identified by conventional maximal assessments.

METHODS

Study design

A randomized, crossover, single-blinded trial was conducted, comprising three laboratory sessions per participant: one familiarization session and two fatiguing sessions (one for each jump type), each including assessments before (PRE) and immediately after (POST) the fatiguing protocol, and separated by a 14-day recovery period (Fig. 1). Participants attended sessions at the same time of day (± 1 hour). They were instructed to maintain their regular training routines but to avoid intensive exercise for two days prior to the fatiguing session. Fatiguing sessions lasted up to 90 min.

The first session served to familiarize participants with the procedures, ensure proper execution of the physical tests, assess tolerance to electrical stimulation, collect anthropometric data, and document sports routines and medical histories. One week later, the first fatiguing jump protocol (either SJ or DJ, randomly assigned) was performed following a standardized warm-up. During the PRE and POST assessments, a standardized sequence of assessments was conducted: rate of perceived pain; two countermovement jumps (CMJ); two quadriceps MVICs; determination of the maximal current intensity (I_{max}) to elicit peak twitch (Pt) (not repeated at POST); two sequences of stimulations at 120% I_{max} : one Pt, one doublet twitch (DT), one DT superimposed (DTsup) onto MVIC, and one potentiated DT (DTpot), in this order; and two 10-seconds submaximal isometric contractions at 50% of MVIC (SubMax50%).

Randomization, concealed allocation, and blinding

Both participants and researchers remained unaware of participant allocation until completion of the pre-fatigue assessment. Before the fatiguing protocol, a researcher presented an opaque envelope containing two identically folded pieces of paper, each labeled internally with one of the two jump conditions. The participant selected and unfolded one paper to reveal the condition to be performed first. Participants and conditions were coded. Torque and EMG data were extracted and processed by a blinded researcher (N.B.). Statistical analyses were then performed by J.C., and the analysis files were returned to the co-authors for inspection. Owing to the nature of the experiment, blinding of participants and researchers involved in data collection was not feasible. To minimize bias, standardized procedures were maintained throughout all sessions, including consistent verbal encouragement during every effort, and participants were not informed of the expected fatigue responses.

Participants

Sixteen healthy, physically active women (mean $\pm$ SD: age, 23.5 ± 6.7 years; height, 164.2 ± 5.0 cm; body mass, 56.6 ± 6.2 kg; body mass index, 20.9 ± 2.2 kg·m⁻²) volunteered to participate. Inclusion criteria were age ≥ 18 years, physical activity > 2 h/week, no musculoskeletal injuries within the previous six months, and no pain or physical limitations affecting performance. Participants primarily engaged in soccer (87.5%; 4.5 ± 0.3 h/week), followed by strength training (37.5%; 5.1 ± 2.1 h/week), running (12.5%; 2.0 ± 1.0 h/week), and badminton (6.25%; 1.5 h/week); multiple responses were allowed. Sample size was determined a priori using G*Power (version 3.1.9.6, Düsseldorf, Germany) assuming $\alpha = 0.05$, power $(1 - \beta) = 0.80$, and effect size = 0.35. The analysis indicated that 16 participants were required, with RMS as the primary outcome. Participants were recruited through verbal communication within the Sport Science Faculty at Université Bourgogne Europe. Before participation, they received a detailed explanation of the study and provided written informed consent. The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee for Sport Science Research.

Warm-up

Participants performed a standardized warm-up consisting of submaximal (50%) concentric (5 repetitions) and eccentric (5 repetitions) lower limb exercises, followed by athletic drills (20 m) and jump variations (5 repetitions). The sequence comprised: single-leg squats, prone self-resisted knee flexion, self-resisted hip flexion, single-leg calf raises, high knees, butt kicks, straight-leg bounds, SJ, DJ, and CMJ.

Fatiguing protocols

The fatiguing protocol consisted of 3 sets of 30 maximal jumps separated by 2 min of rest between sets. Jumps were paced by a custom audio file at one jump every 6 s. Jump height (cm) was monitored using an optoelectronic system (Optojump, Microgate, Bolzano, Italy), with real-time visual feedback provided by the Optojump Next software. Researchers encouraged participants to maximize jump height while maintaining proper technique. Immediately after the final jump, participants rated quadriceps exertion on a 100-mm scale, followed by the neuromuscular assessments in the same order as PRE: two CMJs, two MVICs, two electrical stimulation sequences, and two SubMax50%.

Drop Jump protocol

The DJs were executed from a 40-cm-height bench, with participants standing upright, hands on the hips. The volunteers were instructed to deviate their center of gravity anteriorly while stepping one foot forward and out of the bench, without bending their knees, so letting their body fall onto the interior of the OptoJump bars. Then, by contacting both feet at the same time with the floor, knees extended, they were instructed to absorb the impact rapidly by flexing their knees at 90° degrees and then to jump maximally (as fast and high as they can) with knees straight. Then, they were instructed to avoid bending the knees while absorbing the impact using the calf muscles. After, they returned to the initial position stepping up two 20-cm steps that minimized the concentric effort. During the entire protocol, the volunteers did not remove their hands from hips.

Squat Jump protocol

The SJs were performed from an upright standing position, with feet shoulder-width apart and hands on the hips. The volunteers were instructed to squat at 90° degrees of knee flexion and maintain the position for one second, then jump maximally (as fast and high as they can) with knees straight. Then, they were instructed to absorb the impact without bending the knees, i.e., using the calf muscles. During the entire protocol, the volunteers did not remove their hands from hips.

Neuromuscular measurements

Countermovement jump

To assess maximal jump capacity (jump height in cm), two CMJs (30 s rest) were performed and averaged. The volunteers started standing with both feet approximately at shoulder-width and hands on the hips. The volunteers were instructed to squat at 90° of knee flexion and to subsequently jump maximally (as fast and high as they can) with knees straight. Then, when contacting the ground, they were instructed to absorb the impact without bending the knees. During the jumps, the volunteers did not remove their hands from hips.

Maximal voluntary isometric contraction

Volunteers were seated on an isokinetic dynamometer (Biodex 4 Quickset, Biodex Corporation, Shirley, NY, USA) chair. The rotation axis of the device was aligned with the volunteer's right knee axis, with the knee positioned at 70° of flexion and the hip at 85° (0° = full extension for both joints). The right leg was strapped two digits above the lateral malleolus to the dynamometer lever arm, and upper body movement was restricted by straps across the trunk and waist. Torque signals were recorded synchronously with the EMG signals using an analog-to-digital conversion system (MP150; Biopac Systems Inc., Goleta, CA, USA) operating at a sampling frequency of 2000 Hz and a 30 Hz low-pass filter and displaying curves and values on the software Acqknowledge (AcqKnowledge® 4.2, BIOPAC Systems, Inc., Goleta, CA). Two MVICs separated by 30 s were performed. Each contraction lasted 4 seconds and was performed under strong verbal encouragement. The highest torque achieved was retained for analysis.

Neuromuscular electrical stimulation and Maximal M-wave

A high voltage (400 V), constant current stimulator (DS7A, Digitimer, Hertfordshire, UK) delivered 1-ms pulses as single or doublet (100 Hz) twitches. Two 5 × 9 self-adhesive electrodes (Compex, SA) were placed on the superficial quadriceps femoris muscle bellies. The proximal electrode was placed anterolaterally at approximately 50% of the thigh length, targeting the vastus lateralis and rectus femoris muscles. The distal electrode was placed anteromedially approximately 5 cm above the patellar base, targeting the vastus medialis and rectus femoris muscles. Electrode positioning was individually adjusted to optimize torque and minimize discomfort for a given current intensity, ensuring appropriate targeting of motor points. To ensure consistent electrodes placements across sessions, we used a memory-aiding device for each volunteer made of cardboard pieces. A larger piece (30 cm x 6 cm) was placed on the anterior thigh with its distal edge aligned to the patella base. Smaller pieces, cut in the size of the electrical stimulation electrodes, were attached at the corresponding electrode positions on the larger piece (more details in *Electromyographic Activity Recording* section).

To determine the I_{max} required to evoke the highest torque, a series of single twitches was applied every 5 s, starting at 30 mA and increasing by 10 mA after every two twitches until a torque plateau was reached. To ensure maximal motor unit recruitment, all subsequent stimulations were delivered at 120% of I_{max} : (i) a single twitch to elicit the maximal M-wave (M_{max}) amplitude for EMG normalization, (ii) ~ 3 s later, a DT to assess peripheral fatigue, (iii) ~ 2 s after participants initiated an MVIC, during which a DT_{sup} was applied to assess voluntary activation, and (iv) ~ 3 s after the MVIC ended, a DT_{pot} delivered at rest. The sequence was repeated after a 30 s rest, and the highest torque from each stimulus was used for analysis.

Voluntary activation level

Using the interpolated twitch technique, we calculated the voluntary activation level as a measure of central fatigue, expressed as a percentage. A correction was applied (Strojnik and Komi 1998), which accounts for the mismatch between the torque just before (T_b) the DT_{sup} and the true MVIC. The calculation is expressed as follows:

$$Voluntary\ activation\ level = 100 - (Tb - DT_{sup}) * \frac{\left(\frac{Tb}{MVIC}\right)}{DT_{pot}} * 100$$

Electromyographic activity recording

EMG activity during MVIC, SubMax50%, and electrical stimulation were obtained from the right vastus lateralis using bipolar technique by means of disposable Ag/AgCl electrodes (diameter: 7 mm, interelectrode center to center distance: 20 mm). The skin surface was initially shaved and cleaned with alcohol to ensure low skin impedance (< 5 kW). Pairs of electrodes were placed longitudinally along the muscle fibers at the most prominent region of each muscle belly, identified during a submaximal isometric contraction. A reference electrode was positioned over the ipsilateral patella. To ensure consistent placement across fatigue sessions, distances from electrode centers to the memory-aider border were measured and recorded directly on the device. EMG signals were acquired using the Biopac system with AcqKnowledge software. Raw signals were amplified (gain = 500), then bandpass-filtered (10–500 Hz) and notch-filtered (90–110 Hz) to remove noise artifacts. Vastus lateralis activity was quantified by calculating the root mean square (RMS) over 250 ms sliding windows from the filtered data, using the “biosignalEMG” R package (Guerrero and Macias-Diaz 2018).

Submaximal voluntary isometric contraction

After MVIC procedure, two 10-second SubMax50% were performed with visual feedback displayed on a computer screen. For the post-fatigue protocol assessment, the torque target was adjusted based on the new, fatigued MVIC value. The plateau from each trial was selected for linear variability and complexity analyses of torque and EMG, as described in the *Data Recording and Processing* section.

Rate of Perceived Pain/Exertion

Upon arrival at the laboratory and after completing the fatiguing jumps, perceived quadriceps pain/exertion was assessed using the standardized question: “What is your level of pain/exertion in the thigh muscles?”. A horizontal 100-mm scale with endpoints labeled “no discomfort” and “maximal discomfort” was used. Participants rated their sensation using a vertical slider, with numerical values hidden on the reverse side.

Data Recording and Processing

For each fatigue session, a single AcqKnowledge file was generated containing torque and EMG data, which were analyzed using a custom-written routine in RStudio (Ver. 2023.03.1, Posit Software PBC, Boston, MA, USA). From the MVIC trials, peak torque was extracted. From the SubMax50% trials, mean torque, CV, and SampEn were calculated. For both MVIC and SubMax50% trials, EMG features were analyzed in terms of linear (RMS) and nonlinear metrics (SampEn and the multifractal spectrum descriptors). Additionally, during MVICs only, RMS was normalized (RMS/Mmax).

SampEn, a nonlinear index of signal complexity, was computed using the “TSEntropies” R package (Tomcala 2018). The time series was embedded in an m -dimensional space using time-delay embedding (here $m = 2$). The probability $B^m(r)$, representing the likelihood that two sequences match for m points within a given tolerance r (here $r = 0.2 \cdot \text{standard deviation}$), was estimated by counting matching vector pairs. This process was then repeated for $m + 1$ points to compute $A^m(r)$. SampEn was calculated as the negative natural logarithm of the ratio of these probabilities. Other details of the calculations can be found elsewhere (Babault et al. 2023).

The multifractal spectrum was calculated using the “MFDFA” R package (Laib et al. 2019) following the procedure previously described (Babault et al. 2023). Briefly, the detrended profile was obtained from the cumulative sum of the mean-centered EMG time series and divided into non-overlapping segments. A second-order polynomial ($m = 2$) was fitted to each segment to compute the q th-order fluctuation function, from which the generalized Hurst exponent was estimated and the multifractal spectrum derived. The fluctuation function was computed over timescales ranging from 80 to 300 samples. Only fluctuation functions exhibiting linear behavior ($R^2 > 0.94$) were retained, and the multifractal spectrum was calculated using q values from -10 to $+10$. Six descriptors were then extracted from the singularity spectrum $f(\alpha)$ (Fig. 2). MAX (maximum α exponent) and MIN (minimum α exponent) represent small and large fluctuations, respectively. WIDTH (spectrum width = MAX – MIN) represents the overall strength of multifractality. PEAK (peak exponent), defined as the α value at which $f(\alpha) = 1$, represents the most frequent singularity in the signal. ASYM (asymmetry), calculated as $(\text{PEAK} - \text{MIN})/(\text{MAX} - \text{PEAK})$, indicates whether the spectrum was more influenced by large fluctuations ($\text{ASYM} > 1$) or small fluctuations ($\text{ASYM} < 1$). Finally, PROB (probability index), derived from the vertical difference in fractal dimension (i.e., values on the y axis) between the subsets with maximum and minimum probability, indicates whether the signal was predominantly characterized by large (negative values) or small (positive values) fluctuations.

Statistical Analysis

Statistical analyses were conducted using JASP (version 0.95.4, JASP Team 2025, University of Amsterdam, available free at <https://jasp-stat.s.org/download/>). Data normality was confirmed via the Shapiro-Wilk test. A two-way repeated-measures analysis of variance (ANOVA) (Condition [SJ, DJ] $\times$ Time [PRE, POST]) assessed fatigue-related changes in main conventional and complexity variables. Jump height during fatigue protocols was analyzed separately for SJ and DJ using one-way repeated-measures ANOVAs, avoiding direct between-protocol comparisons due to technical differences. The 30 jumps were grouped into six blocks of five per set (results detailed in Supplemental Material 1). Sphericity was verified using Mauchly’s test, with a Greenhouse-Geisser correction applied for violations. Significant main effects or interactions were explored using Bonferroni post hoc tests ($p < 0.05$). Effect sizes were determined using partial eta squared (η^2) for ANOVAs (small ≥ 0.01 , medium ≥ 0.06 , large ≥ 0.14) and Cohen’s d for significant pairwise comparisons (small ≥ 0.20 , medium ≥ 0.50 , large ≥ 0.80).

RESULTS

For all significant interactions, PRE values were not different between conditions ($p = .65 - 1.0$, $d = -0.17 - 0.26$). Descriptive statistics and statistical significances are provided in Table 1, while Box 1 provides a visual overview of statistical effects.

Table 1

– Descriptive (mean $\pm$ SD) and post hoc results (for significant interactions) for linear and nonlinear measures pre- and post-fatigue induced by squat jump and drop jump

Variable	Squat Jump				Drop Jump			
	MVIC		Submax (50%)		MVIC		Submax (50%)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Voluntary performance								
Voluntary Isometric Contraction, N.m	188.52 $\pm$ 39.61	183.85 $\pm$ 38.94	86.36 $\pm$ 18.41	85.68 $\pm$ 19.06	181.58 $\pm$ 32.90	163.71 $\pm$ 40.54*	84.73 $\pm$ 17.22	75.42 $\pm$ 21.47*
Voluntary Activation Level, %	90.00 $\pm$ 8.87	86.01 $\pm$ 9.57	—	—	89.30 $\pm$ 10.91	87.01 $\pm$ 12.04	—	—
Counter Movement Jump, cm	26.87 $\pm$ 6.01	27.73 $\pm$ 5.58	—	—	27.17 $\pm$ 5.76	25.67 $\pm$ 5.05*	—	—
Torque variability								
CV of Torque, %	—	—	1.84 $\pm$ 0.71	2.05 $\pm$ 1.06	—	—	1.73 $\pm$ 0.70	2.84 $\pm$ 1.28**#
Entropy of Torque	—	—	0.031 $\pm$ 0.01	0.039 $\pm$ 0.02	—	—	0.037 $\pm$ 0.01	0.028 $\pm$ 0.01*
Signal complexity								
Entropy of EMG	0.26 $\pm$ 0.11	0.27 $\pm$ 0.09	0.74 $\pm$ 0.07	0.73 $\pm$ 0.07	0.29 $\pm$ 0.10	0.28 $\pm$ 0.08	0.73 $\pm$ 0.06	0.74 $\pm$ 0.06
MAX	2.14 $\pm$ 0.15	2.11 $\pm$ 0.19	1.99 $\pm$ 0.08	2.01 $\pm$ 0.06	2.22 $\pm$ 0.28	2.08 $\pm$ 0.18	1.95 $\pm$ 0.03	1.97 $\pm$ 0.07
MIN	1.69 $\pm$ 0.14	1.71 $\pm$ 0.11	1.70 $\pm$ 0.08	1.71 $\pm$ 0.09	1.66 $\pm$ 0.14	1.67 $\pm$ 0.09	1.71 $\pm$ 0.07	1.65 $\pm$ 0.14
PEAK	1.91 $\pm$ 0.11	1.89 $\pm$ 0.13	1.90 $\pm$ 0.05	1.91 $\pm$ 0.04	1.92 $\pm$ 0.13	1.86 $\pm$ 0.08	1.90 $\pm$ 0.02	1.86 $\pm$ 0.05*
WIDTH	0.45 $\pm$ 0.13	0.39 $\pm$ 0.18	0.28 $\pm$ 0.12	0.29 $\pm$ 0.10	0.55 $\pm$ 0.30	0.41 $\pm$ 0.18	0.28 $\pm$ 0.09	0.29 $\pm$ 0.14
ASYM	1.08 $\pm$ 0.47	0.99 $\pm$ 0.76	2.72 $\pm$ 2.12	2.39 $\pm$ 1.62	1.10 $\pm$ 0.72	0.96 $\pm$ 0.43	2.80 $\pm$ 2.27	2.91 $\pm$ 2.28

Legend: *p < 0.05; **p < 0.001; #POST-DJ significantly modified considering POST-SJ; dash = not tested; EMG: electromyography; MVIC: maximal voluntary isometric contraction; Submax: submaximal isometric contraction at 50% of MVIC; RMS: mean square; Mmax: Maximal M-wave; CV: coefficient of variation. Multifractal descriptors: MAX (maximum), MIN (minimum), PEAK, WIDTH, ASYM (asymmetry), and PROB (probability).

PROB	0.04 ± 0.21	0.06 ± 0.22	-0.23 ± 0.13	-0.25 ± 0.26	0.07 ± 0.30	0.10 ± 0.19	-0.29 ± 0.18	-0.36 ± 0.16
EMG amplitude								
RMS, mV	0.018 ± 0.013	0.018 ± 0.012	0.002 ± 0.001	0.003 ± 0.004	0.018 ± 0.013	0.020 ± 0.016	0.002 ± 0.001	0.004 ± 0.002
RMS/Mmax	0.001 ± 0.001	0.001 ± 0.000	—		0.001 ± 0.001	0.002 ± 0.002	—	
Mmax, mV	10.55 ± 4.62	11.48 ± 4.29	—		12.24 ± 2.10	12.14 ± 2.17	—	
Maximal evoked torque								
Twitch, N.m	30.74 ± 7.53	24.13 ± 5.68**	—		28.79 ± 7.38	18.04 ± 8.08**#	—	
Doublet twitch, N.m	57.12 ± 10.39	49.30 ± 8.95**	—		55.58 ± 12.42	41.07 ± 11.81**#	—	
Potentiated doublet twitch, N.m	61.90 ± 9.93	53.17 ± 9.88**	—		60.07 ± 12.01	44.67 ± 11.88**#	—	
Legend: *p < 0.05; **p < 0.001; #POST-DJ significantly modified considering POST-SJ; dash = not tested; EMG: electromyography; MVIC: maximal voluntary isometric contraction; Submax: submaximal isometric contraction at 50% of MVIC; RMS: mean square; Mmax: Maximal M-wave; CV: coefficient of variation. Multifractal descriptors: MAX (maximum), MIN (minimum), PEAK, WIDTH, ASYM (asymmetry), and PROB (probability).								

Box 1 – Visual overview of statistical effects (interaction and main effects) on linear and nonlinear neuromuscular measures after fatigue from squat jump and drop jump								
Variable	Interaction (Jump vs. Time)				Overall fatigue (Time effect)		Jump effect	
	After Squat Jump		After Drop Jump					
	MVIC	Submax	MVIC	Submax	MVIC	Submax	MVIC	Submax
Voluntary performance (linear)								
Voluntary Isometric Contraction	•	•	↓ [#]	↓	—	—	—	—
Voluntary Activation Level	•	•	•	•	•	•	•	•
Counter Movement Jump	•	—	↓ [#]	—	—	—	—	—
Torque variability								
CV of Torque (linear)	—	•	—	↑↑↑ [#]	—	—	—	—
Entropy of Torque (nonlinear)	—	•	—	↓	—	•	—	•
EMG complexity								
Entropy of EMG	•	•	•	•	•	•	•	•
MAX	•	•	•	•	•	•	•	SJ > DJ ^{**}
MIN	•	•	•	•	•	•	•	•
PEAK	•	•	•	↓	•	—	•	—
WIDTH	•	•	•	•	•	•	•	•
ASYM	•	•	•	•	•	•	•	•
PROB	•	•	•	•	•	•	•	•
Legend: ↑ or ↓ = significant increase or decrease; vertical arrows indicate the strength of statistical significance (single: $p < 0.05$; double: $p < 0.01$; triple: $p < 0.001$); • = no significant change; dash = not tested; SJ > DJ = squat jump significantly greater than drop jump ($p < 0.01$); # = POST-DJ significantly modified considering POST-SJ. EMG: electromyography; MVIC: maximal voluntary isometric contraction; Submax: submaximal isometric contraction at 50% of MVIC; RMS: root mean square; Mmax: Maximal M-wave; CV: coefficient of variation. Multifractal descriptors: MAX (maximum), MIN (minimum), PEAK, WIDTH, ASYM (asymmetry), and PROB (probability).								

Box 1 – Visual overview of statistical effects (interaction and main effects) on linear and nonlinear neuromuscular measures after fatigue from squat jump and drop jump								
EMG amplitude (linear)								
RMS	•	•	•	•	•	↑↑	•	•
RMS/Mmax	•	—	•	—	•	—	•	—
Mmax	•		•		•		•	
Maximal Evoked torque (linear)								
Twitch	↓↓↓		↓↓↓ [#]		—		—	
Doublet twitch	↓↓↓		↓↓↓ [#]		—		—	
Potentiated doublet twitch	↓↓↓		↓↓↓ [#]		—		—	
Legend: ↑ or ↓ = significant increase or decrease; vertical arrows indicate the strength of statistical significance (single: $p < 0.05$; double: $p < 0.01$; triple: $p < 0.001$); • = no significant change; dash = not tested; SJ > DJ = squat jump significantly greater than drop jump ($p < 0.01$); # = POST-DJ significantly modified considering POST-SJ. EMG: electromyography; MVIC: maximal voluntary isometric contraction; Submax: submaximal isometric contraction at 50% of MVIC; RMS: root mean square; Mmax: Maximal M-wave; CV: coefficient of variation. Multifractal descriptors: MAX (maximum), MIN (minimum), PEAK, WIDTH, ASYM (asymmetry), and PROB (probability).								

Rate of perceived pain/exertion

There was an interaction between Condition and Time ($F = 6.56$, $p = .022$, η^2 : 0.30) for the rate of perceived pain/exertion. Participants began the fatiguing session reporting pain/exertion of 1.75 ± 4.32 and 3.62 ± 4.87 for SJ and DJ, respectively. After completion of the fatiguing protocol, it increased significantly to 13.31 ± 11.47 mm ($p = .009$, $d = -1.07$) and 22.50 ± 17.01 mm ($p = .001$, $d = -1.75$), respectively. Values of POST-DJ were significantly higher than POST-SJ ($p = .044$, $d = -0.85$) (Fig. 3).

Fatigue during maximal contractions

Evoked torque

There was an interaction between Condition and Time for the Pt ($F = 9.23$, $p = .008$, η^2 : 0.38), DT ($F = 15.47$, $p = .001$, η^2 : 0.50), and DTpot ($F = 12.99$, $p = .003$, η^2 : 0.46). Pos hoc analyses review the same pattern across these stimulation techniques: reduced evoked torque for SJ ($p < .001$, $d = 0.71$ – 0.91) at POST compared to PRE, as well as for DJ ($p < .001$, $d = 1.32$ – 1.48). Moreover, values POST-DJ were consistently lower than POST-SJ ($p = .002$ – $.006$, $d = 0.75$ – 0.84).

Voluntary Performance

There was a Condition $\times$ Time interaction for MVIC ($F = 4.72$, $p = .046$, η^2 : 0.23, Fig. 4a). Post hoc analysis showed lower torque at POST compared to PRE for DJ ($p = .017$, $d = 0.46$), but not for SJ ($p = .496$, $d = 0.12$). Moreover, POST-DJ was lower than POST-SJ ($p = .036$, $d = 0.52$). For voluntary activation level, there was no Condition $\times$ Time interaction ($F = 0.33$, $p = .57$, η^2 : 0.02), Condition effect ($F = 0.005$, $p = .94$, $\eta^2 < 0.001$), or Time effect ($F = 2.75$, $p = .118$, η^2 : 0.15). For CMJ height, there was a significant interaction between Condition and Time ($F = 19.80$, $p < .001$, $\eta^2 = 0.56$). Post hoc comparisons revealed that CMJ significantly decreased from PRE to POST for DJ ($p = .02$, $d = 0.26$), but not for SJ ($p = .68$, $d = 0.15$). The difference between DJ and SJ at POST was also significant ($p = .040$, $d = 0.36$), being lower after DJ.

EMG during MVIC

For RMS, there was no interaction ($F = 0.10$, $p = .756$, η^2 : 0.007), Condition effect ($F = 0.29$, $p = .597$, η^2 : 0.01), or Time effect ($F = 0.54$, $p = .473$, η^2 : 0.03). For RMS/Mmax, no interaction ($F = 0.33$, $p = .572$, η^2 : 0.02), Condition effect ($F = 0.28$, $p = .603$, η^2 : 0.01), or Time effect ($F = 0.37$, $p = .549$, η^2 : 0.02) were observed. Also, for Mmax, no interaction ($F = 0.39$, $p = .539$, η^2 : 0.02), Condition effect ($F = 1.87$, $p = .191$, η^2 : 0.11), or Time effect ($F = 0.29$, $p = .595$, η^2 : 0.01) were observed.

For EMG SampEn, no interaction ($F = 0.28$, $p = .601$, η^2 : 0.01), Condition effect ($F = 0.39$, $p = .540$, η^2 : 0.02), or Time effect ($F = 0.006$, $p = .942$, η^2 : < 0.001) were observed.

None of the EMG MFDFA variables (MAX, MIN, PEAK, WIDTH, ASYM, PROB) showed a significant interaction ($F < 0.02$ to 2.70, $p = .121 - .989$, η^2 : < 0.001 to 0.15) or main effects ($F < 0.001 - 4.21$, $p = .058 - .976$, η^2 : < 0.001 to 0.24).

Fatigue during submaximal contractions

Torque

There was a Condition $\times$ Time interaction for torque during SubMax_{50%} ($F = 9.77$, $p = .007$, η^2 : 0.39, Fig. 4b). Post hoc analysis showed lower torque at POST compared to PRE for DJ ($p = .019$, $d = 0.48$), but not for SJ ($p = 1.0$, $d = 0.03$). POST-DJ was not statistically lower than POST-SJ ($p = .060$, $d = 0.53$).

Torque variability (CV), showed a Condition $\times$ Time interaction ($F = 12.05$, $p = .003$, η^2 : 0.44, Fig. 4c). Post hoc analysis demonstrated increased CV during POST compared to PRE for DJ ($p < .001$, $d = 1.13$), but not for SJ ($p = 1.0$, $d = 0.21$). Moreover, POST-DJ variability was greater than POST-SJ ($p = .009$, $d = 0.81$).

A significant interaction between Condition and Time was observed for torque SampEn ($F = 5.07$, $p = .040$, $\eta^2 = 0.25$, Fig. 4d). Post hoc comparisons revealed a significant reduction in entropy from PRE to POST for DJ ($p = .047$, $d = 0.54$), but not for SJ ($p = 1.0$, $d = 0.44$). No significant difference was found between DJ and SJ at POST ($p = .88$, $d = 0.63$).

EMG during submaximal contraction

There was no interaction between Condition and Time for RMS during SubMax_{50%} ($F = 0.05$, $p = .811$, η^2 : 0.004). However, there was a main effect of Time ($F = 11.75$, $p = .004$, η^2 : 0.43), where RMS were higher for POST compared to PRE ($p = .004$, $d = 0.58$). There was no main effect of Condition ($F = 0.10$, $p = .751$, η^2 : 0.007).

During SubMax_{50%}, no interaction ($F = 3.03$, $p = .102$, η^2 : 0.16), Condition effect ($F_{1,15} = 0.04$, $p = .843$, η^2 : 0.003), or Time effect ($F = 0.56$, $p = .465$, η^2 : 0.03) were observed for SampEn.

During SubMax_{50%}, most MFDFA variables (MIN, WIDTH, ASYM, AND PROB) also yielded no significant interaction ($F < 0.001$ –3.81, $p = .07$ – .978, η^2 : < 0.001 –0.20). Moreover, no significant main effect was also obtained ($F = 0.01$ –4.39, $p = .053$ – .915, η^2 : < 0.001 –0.22). In contrast, for PEAK, there was an interaction between Condition and Time ($F = 7.87$, $p = .013$, η^2 : 0.34). Post hoc analysis revealed a significant decrease from PRE to POST for DJ ($p = .016$, $d = 0.90$), whereas no change was found for SJ ($p = 1.0$, $d = 0.23$). The lower POST value for DJ did not reach statistical significance compared with SJ ($p = .057$, $d = 0.97$). For MAX, there was no Condition $\times$ Time interaction ($F = 0.006$, $p = .939$, η^2 : < 0.001) or time effect ($F = 2.14$, $p = .164$, η^2 : 0.12), but there was a main effect of Condition ($F = 10.29$, $p = .006$, η^2 : 0.40), with post hoc analysis indicating lower values for DJ compared to SJ ($p = .006$, $d = 0.56$).

DISCUSSION

This study compared fatigue responses to concentric-dominant (SJ) and plyometric (DJ) protocols using conventional neuromuscular measures and complexity-based analyses in healthy women. Conventional assessments showed that only DJ reduced MVIC and CMJ performance, whereas evoked torque decreased after both protocols, with a greater reduction following DJ. Mmax and voluntary activation level remained unchanged, suggesting preserved muscle membrane excitability and voluntary activation. EMG RMS was also unchanged during MVIC but increased during SubMax50% after both protocols, indicating that greater muscle activation was required to maintain the same submaximal torque. During SubMax50%, torque CV increased only after DJ, indicating greater variability in torque output, while torque SampEn decreased, suggesting a more regular pattern of force production. Complexity-based analyses of the EMG further revealed task-specific alterations: MFDFA-derived PEAK and MAX decreased only during SubMax50% following DJ, whereas EMG SampEn remained unchanged during both MVIC and SubMax50%. Collectively, these findings indicate that submaximal contractions combined with variability and complexity-based analyses can reveal fatigue-related alterations in neuromuscular control that may not be captured by conventional maximal assessments.

Fatigue during maximal isometric contractions

Peripheral fatigue was evident after both SJ and DJ, but was more pronounced after DJ, with consistent greater reductions in evoked torque. Unchanged Mmax indicated preserved neuromuscular

transmission, suggesting that fatigue stemmed from impaired excitation–contraction coupling and/or contractile protein dysfunction (Wan et al. 2017). Given the greater mechanical loading associated with DJ, EIMD may have contributed to these responses (Tofas et al. 2008).

Central fatigue was not evident, as voluntary activation level remained stable, consistent with previous observations following plyometric exercise (Drinkwater et al. 2009). Consistent with these findings, prior research shows that 100 DJs markedly reduce evoked torque but produce only a modest decline in MVIC (Skurvydas et al. 2007). Furthermore, because our sample comprised only women, who are generally less fatigable than men (Hunter 2014), the protocol may have elicited a lower overall fatigue response.

Compensatory neural responses to peripheral fatigue typically involve increased motor unit recruitment, higher discharge rates, and greater motor unit synchronization (Garland et al. 1994). Consequently, MVIC EMG amplitude may increase initially (Cavalcante et al. 2022), decrease with central fatigue (Boccia et al. 2018) or remain unchanged (Ortega-Auriol et al. 2018), highlighting the complexity of interpreting surface EMG signals (Dimitrova and Dimitrov 2003). Here, RMS, RMS/M, EMG SampEn, and MFDFA remained unchanged following fatigue. Alongside preserved voluntary activation level, this suggests maintained maximal neural drive and temporal organization of motor unit activity. While fatigue typically decreases SampEn (reflecting synchronization and reduced firing variability) and alters MFDFA descriptors (like an increased scaling exponent α due to reduced activation) during sustained contractions (Hernandez and Camic 2019), we observed no such changes. Likewise, previous studies have reported fatigue-related alterations in MFDFA descriptors during sustained isometric contractions, including an increased DFA scaling exponent α , possibly associated with reduced motor unit activation (Hernandez and Camic 2019). Therefore, despite greater DJ-induced peripheral fatigue, neither amplitude- nor complexity-based EMG metrics indicated altered neural activation during MVIC.

The unchanged conventional and complexity-based EMG markers during MVIC may have two complementary explanations. First, the level of fatigue was probably insufficient. Central and peripheral fatigue typically co-occur only near critical torque, the threshold beyond which fatigue accumulates rapidly, whereas below this level fatigue remains predominantly peripheral. This threshold is harder to reach during intermittent jumping than sustained contractions (Madeleine et al. 2002; Pethick et al. 2016, 2021). Because our protocols likely remained below this threshold, maximal torque declined by only ~ 2.5% after SJ and ~ 9.8% after DJ, remaining below the 13.7–17.9% decrements previously associated with reduced EMG complexity (Hernandez and Camic 2019). Second, MVIC presents a ceiling effect; near-maximal neural drive limits the sensitivity of EMG metrics to subtle adjustments. Furthermore, unlike isolated single-muscle tasks, jumping induces multi-muscle fatigue involving systemic cardiovascular and thermoregulatory responses that further modulate neuromuscular behavior (Arazi et al. 2016; Davies and Young 1983; Davies et al. 2015; Stewart et al. 2003). Additionally, jump-induced facilitatory effects, akin to warm-up or stretch potentiation (Babault et al. 2022; Davies and Young 1983), may have counterbalanced expected complexity reductions (Davies and Young 1983). Consequently, maximal contractions may lack the sensitivity to detect neural adjustments following SSC exercise, supporting the assessment of submaximal contractions to provide additional information.

Fatigue during submaximal isometric contractions

Post-DJ torque variability increased, as shown by higher CV, indicating impaired motor control (Vaillancourt and Newell, 2003). Consequently, SSC-induced fatigue may impair tasks requiring precise force production, such as submaximal athletic or rehabilitation exercises, by temporarily reducing accuracy (Pethick and Tallent 2022). However, magnitude-based metrics like CV overlook force dynamics, which are captured by temporal signal structure. Consistent with previous findings (Pethick et al. 2015), post-fatigue torque SampEn decreased, demonstrating that greater variability coincided with higher signal regularity—reflecting reduced complexity and adaptability rather than mere force fluctuations (Babault et al. 2024; Pethick and Tallent 2022). Mechanistically, this stems from increased group III/IV muscle afferent feedback (Hureau et al. 2018; Jones et al. 2008), which alters motor unit recruitment and discharge rate (Martinez-Valdes et al. 2020) and increasing common synaptic input to the motor neuron pool (Castronovo et al. 2015). Reduced Ia afferent facilitation (Macefield et al. 1991), reinforced by group III/IV presynaptic inhibition (Taylor et al. 2016), may further restrict output flexibility. Finally, reduced torque complexity relates to metabolic pathway shifts, though exact mechanisms remain unclear (Pethick et al. 2016; Seely and Macklem 2012).

As for MVIC, EMG SampEn did not change significantly with fatigue during SubMax50%. This aligns with Troiano et al. (Troiano et al. 2008), who reported unchanged entropy over time during a sustained 50% MVIC trapezius contraction. The authors suggested that EMG entropy reflects muscle force level rather than fatigue state. Supporting this, our EMG SampEn values were ~ 2.5 times higher during SubMax50% than MVIC, indicating greater signal complexity during submaximal efforts. Key MFDFA descriptors also align with this pattern; for example, PROB mean values were positive for MVIC but negative for SubMax50%, indicating predominant larger fluctuations during submaximal contractions. This result is expected given lower motor unit synchronization under submaximal conditions (Garland et al. 1994).

During SubMax50%, MFDFA and RMS revealed distinct fatigue responses undetected during MVIC. PEAK was the most responsive multifractal metric, showing a significant interaction and a sharper post-DJ decline. This reflects a shift toward larger, more irregular temporal EMG fluctuations, potentially indicating increased variability in motor unit recruitment. Conversely, RMS increased only as a main effect of time, failing to differentiate between SJ and DJ. These results suggest complexity analysis may better inform neural modulations generating muscle force (Rampichini et al. 2020; Sun et al. 2022). However, a reduction in PEAK indicates increased complexity, which is not expected with fatigue. While a reduction in PEAK indicates increased complexity, a response typically unexpected with fatigue, this might reflect enhanced neural modulation to avoid further damage in response to altered muscle afferent feedback from fiber disruption (Taylor et al. 2000).

Limitations

Our study has some limitations. Complexity measures are often more sensitive at lower contraction intensities (10–30%) (Beretta-Piccoli et al. 2018) yet altered EMG patterns were still detectable at the relatively high submaximal intensity adopted here (50% MVIC), including a main effect of condition for

MAX and statistical trends for WIDTH during MVIC and PROB during SubMax50%. Future studies should explore various intensities to optimize fatigue detection for applied submaximal contexts. Methodologically, using a fixed absolute torque rather than a relative target might better isolate neural contributions. Furthermore, visual and verbal feedback during SubMax50% may have influenced motor control, suggesting future designs should consider eyes-closed conditions to better isolate proprioception. We also did not assess torque DFA, which captures mechanical complexity changes and could complement our finding that torque SampEn decreased post-DJ despite unchanged EMG SampEn. Finally, direct evidence linking signal complexity changes to exact neurophysiological mechanisms, such as increased motor unit synchronization, remains absent and requires further experimental confirmation.

CONCLUSION

Our findings demonstrate that SSC exercises induce peripheral fatigue that fundamentally alters the central nervous system's control strategy. While conventional maximal assessments often mask these subtle neural adjustments, evaluating submaximal contractions through complexity-based analyses reveals a distinct loss of force adaptability and an altered temporal organization of motor unit recruitment. From a broader physiological perspective, this suggests that the neuromuscular system compensates for localized muscle impairment by reorganizing its neural output to maintain steady force generation. Because submaximal efforts more closely reflect the actual physiological demands of most athletic and daily activities, moving beyond traditional maximal tests to incorporate complexity analyses provides a more sensitive and ecologically valid approach to evaluating neuromuscular function. Ultimately, this comprehensive methodology offers valuable insights for optimizing training load management, monitoring cumulative fatigue, and guiding rehabilitation strategies.

Abbreviations

ANOVA

Analysis of variance

ASYM

Asymmetry

CMJ

Countermovement jumps

CV

Coefficient of variation

DJ

Drop jumps

DOMS

Delayed-onset muscle soreness

DT

Doublet twitch

DTpot

Potentiated doublet twitch
DTsup
Doublet twitch superimposed onto maximal voluntary isometric contraction
EMG
Electromyography
I_{max}
Maximal current amplitude
MAX
Maximum α exponent
MFDFA
Multifractal detrended fluctuation analysis
MIN
Minimum α exponent
M_{max}
Maximal M-wave
MVIC
Maximal voluntary isometric contraction
PEAK
Peak exponent
PROB
Probability index
P_t
Peak twitch
RMS
Root mean square
SampEn
Sample entropy
SJ
Squat jumps
SSC
Stretch-shortening cycle
SubMax50%
Submaximal isometric contractions at 50% of MVIC
T_b
Torque just before the superimposed doublet twitch
WIDTH
Spectrum width

Declarations

Compliance with Ethical Standards

This study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee for Sport Science Research. Before participation, all participants received a detailed explanation of the study and provided written informed consent.

Competing Interests

The authors declare no competing interests.

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Author Contribution

Conceptualization: C.C., N.B.; Methodology: J.G.T.C., L.P.P., M.B., C.C., J.L.Q.D., N.B.; Investigation: J.G.T.C., L.P.P.; Formal analysis: J.G.T.C., L.P.P., N.B.; Writing – original draft: J.G.T.C.; Writing – review and editing: J.G.T.C., L.P.P., M.B., C.C., J.L.Q.D., N.B. All authors read and approved the final manuscript.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

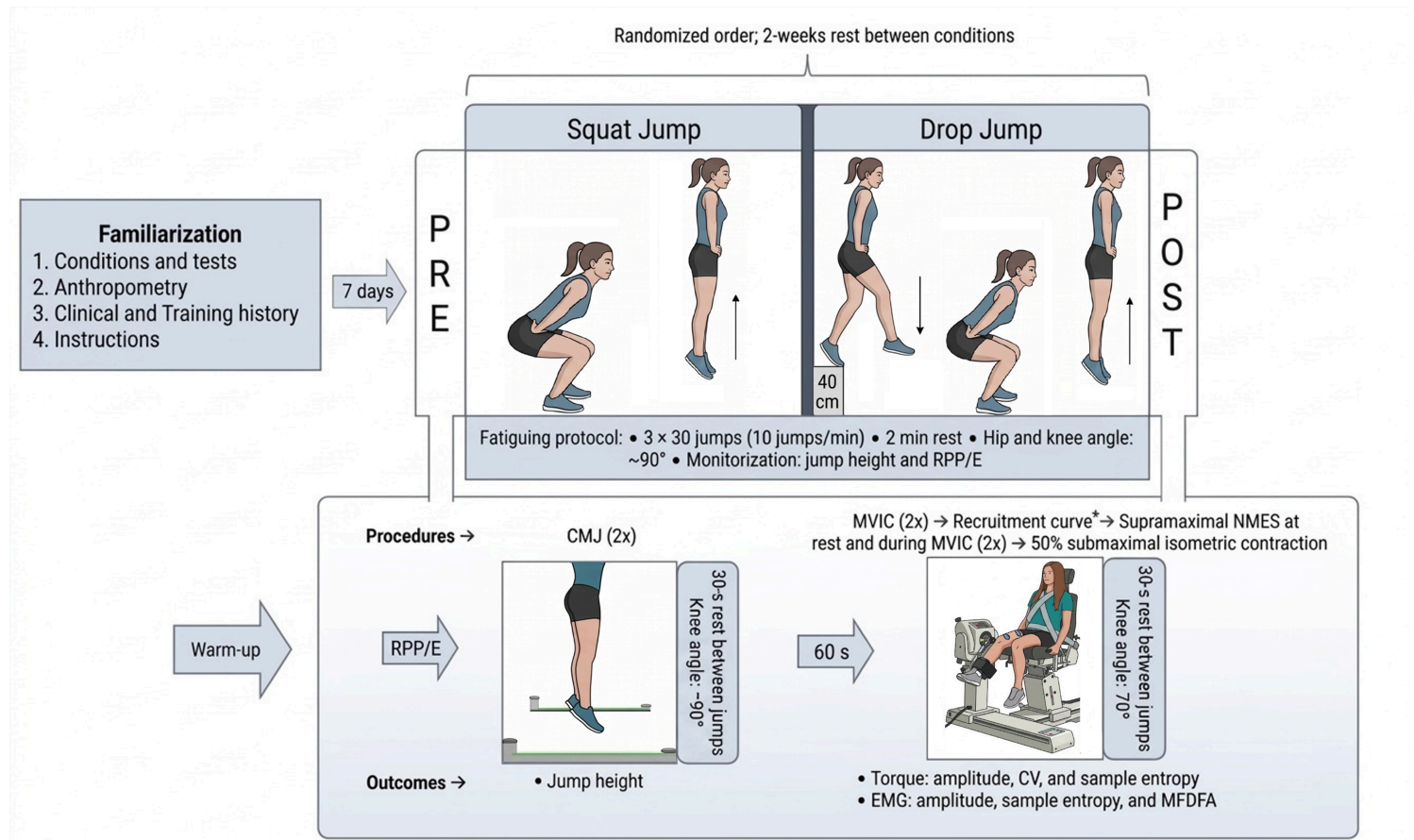


Figure 1

Illustration of the experimental design. Female volunteers attended three laboratory sessions: one familiarization and two experimental sessions, separated by a 2-week rest period. Seven days after familiarization, participants performed a fatiguing protocol (either squat jumps or drop jumps, in randomized order) with assessments conducted pre- and post-fatigue protocol. The assessment procedures consisted of a warm-up, measurement of the rate of perceived pain or exertion (RPP/E),

countermovement jump (CMJ) height, and torque and electromyography (EMG) variables obtained from voluntary and evoked contractions. **Legend:** MVIC, maximal voluntary isometric contraction; NMES, neuromuscular electrical stimulation; CV, coefficient of variation; MFDFA, multifractal detrended fluctuation analysis. * indicates procedures performed only at the pre-fatigue moment

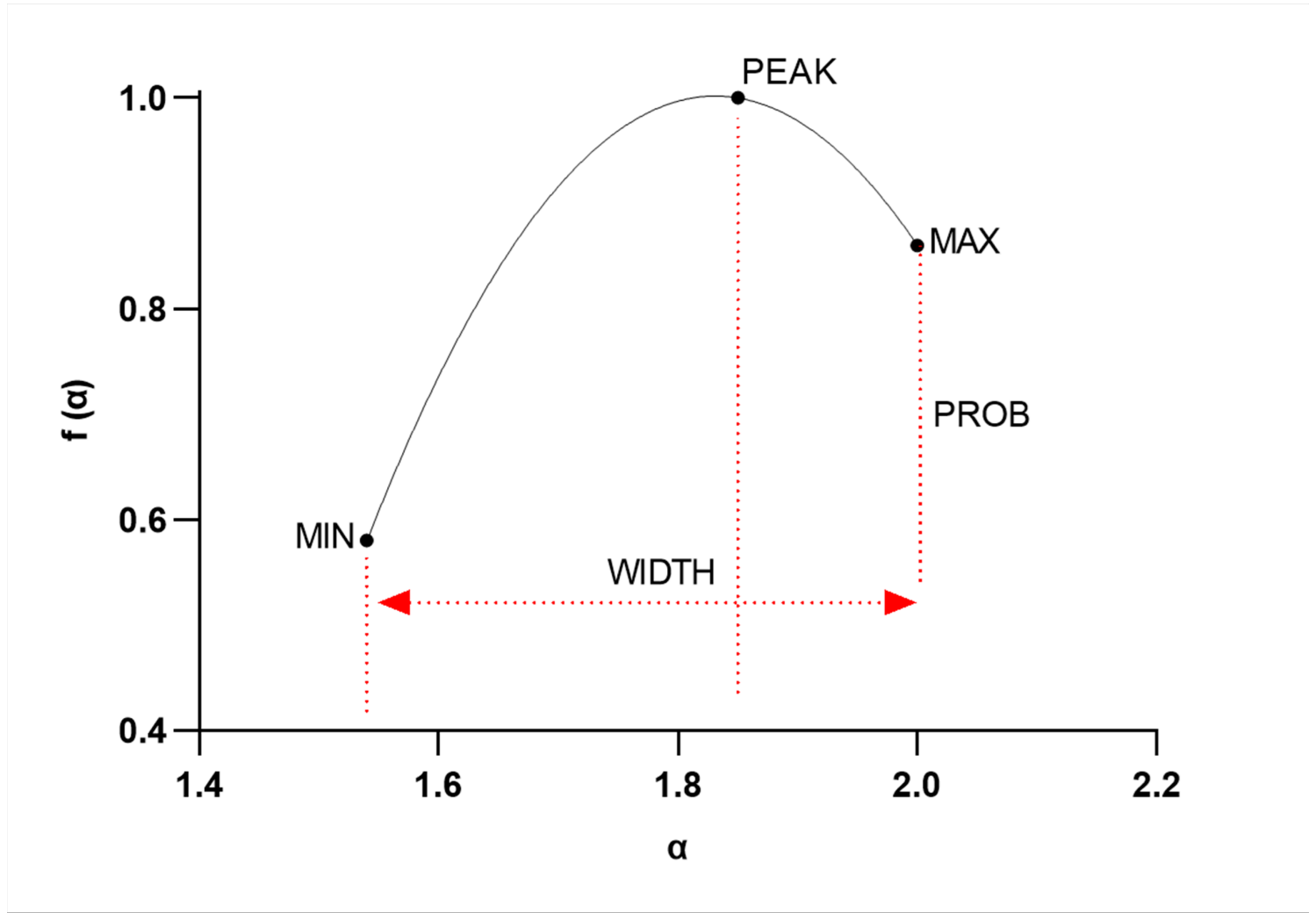


Figure 2

Illustration of the EMG multifractal spectrum during a submaximal quadriceps contraction at 50% of maximal voluntary isometric contraction. MAX is the maximum α exponent; MIN is the minimum α exponent; WIDTH is the total spectrum width (MAX – MIN); PEAK is the singularity exponent at the spectrum peak, defined as the α value at which $f(\alpha) = 1$; PROB is calculated from the difference in fractal dimension (i.e., values on the y-axis) between the subsets with maximum and minimum probability; Asymmetry (not shown) is calculated as $(\text{PEAK} - \text{MIN})/(\text{MAX} - \text{PEAK})$

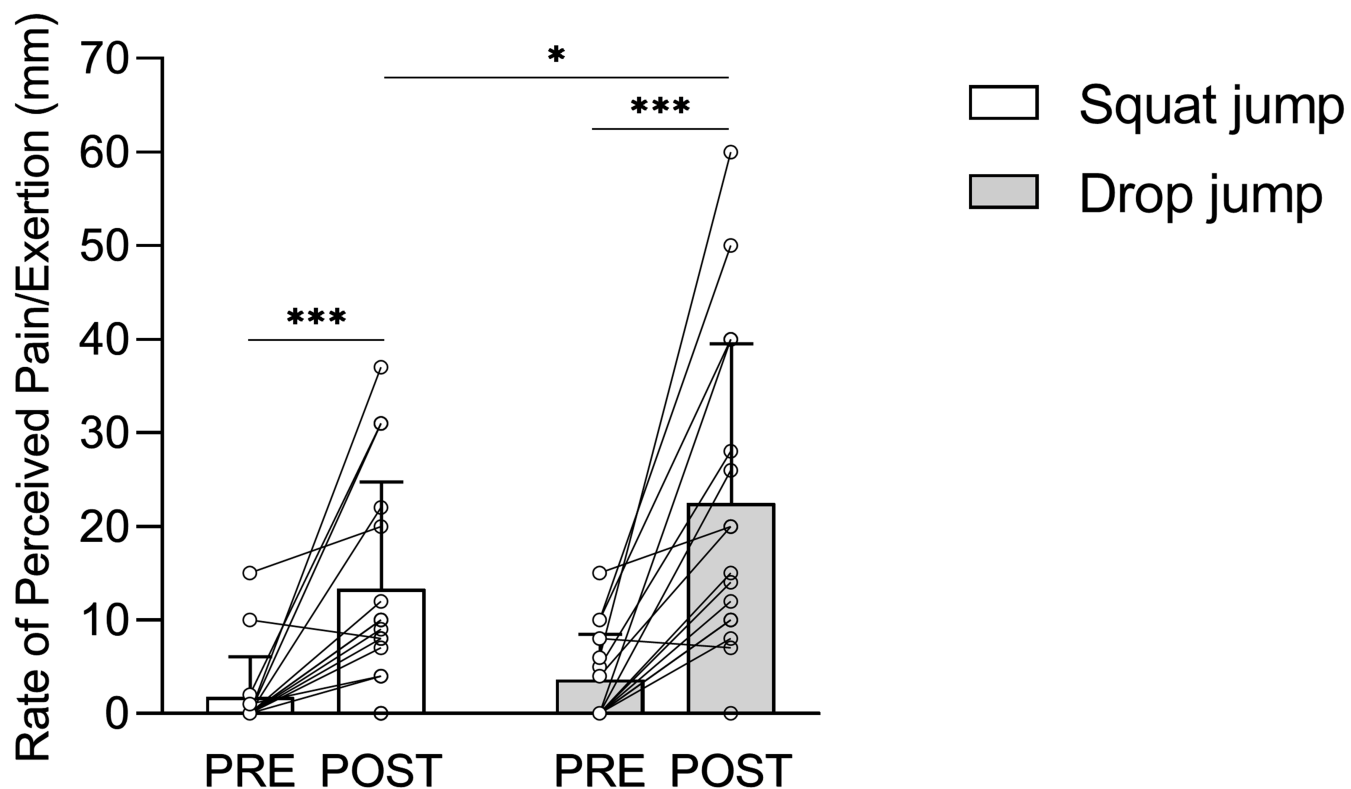


Figure 3

Rate of perceived pain/exertion before (PRE) and immediately after (POST) the fatiguing squat jump and drop jump protocols. Legend: Single and triple asterisks indicate $p < 0.05$ and $p < 0.001$, respectively

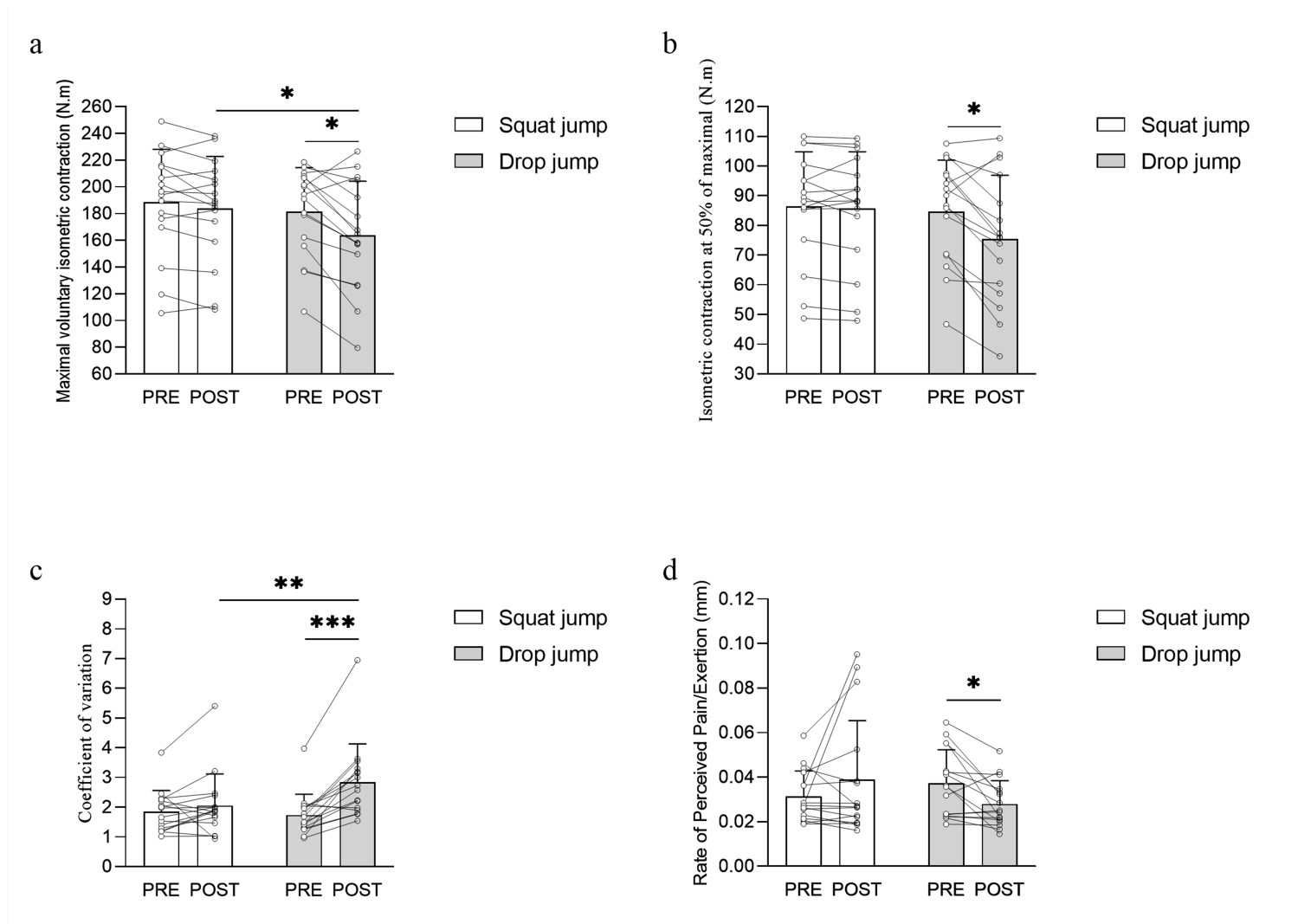


Figure 4

Linear and complexity-based analyses during maximal and submaximal voluntary isometric contractions before (PRE) and immediately after (POST) the fatiguing squat jump (SJ) and drop jump (DJ) protocols. Single, double, and triple asterisks indicate $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively

Supplementary Files

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