Functional multilevel modelling of the influence of the menstrual cycle on the performance of female cyclists

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Abstract: The relation between hormonal fluctuations along menstrual cycles and physical performance is of particular interest in sport science research. With the development of sensors technologies, the recording of large scale, high frequency performance data sets is now available. For cycling, performance can be measured using Mean Maximal Power curve. A functional linear mixed model is proposed to assess whether performance differs between phases of the menstrual cycle and how performance varies over the cycle based on the athletes, training intensities and types of the bike. Our methodology captures the continuous dynamic change characteristic of the data. The results indicate no difference in average performance between the phases. The performance variability is also similar for each phase. Most of the performance variability is induced by the differences between the athletes.

Keywords: Cycling; Functional Data Analysis; Menstrual Cycle; Mixed-effects Model; Performance Analysis

1 Introduction

Menstrual cycles affect women's health and wellness. Female sex hormones, and especially, estradiol and progesterone, fluctuate along the menstrual cycle (see Figure 1). These hormones affect multiple parameters on women ranging from adverse symptoms, such as fatigue, sleep disturbance or mood disorders along menstrual cycle phases (Pierson et al., 2021), to many beneficial cardiovascular, muscular and metabolic pa- rameters (Meignié et al.,

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2021). Performance-based research in women sport science is still scarce in regards to the influence of menstrual cycle phases (Meignié et al, 2021). Cycling is interesting to analyze the influence of hormonal fluctuation onto female performance. Mobile power meters are fitted to bicycles to measure the power delivered by cyclists during training. These data can be used to monitor and evaluate training performance. Mean Maximal Power (MMP) curves have been introduced to analyze power output profile at the individual level (Pinot and Grappe, 2010). MMP curves are defined as the maximal amount of power a cyclist can produce in a given period of time. We analyse whether performance, in terms of MMP, is influenced by the menstrual phases. We study performance variability with respect to menstrual cycle phases, athletes, rating of perceived exertion (RPE) using the Borg-CR10 scale (Borg, 1982) and types of the bike. We developed a functional linear mixed model to answer these questions.

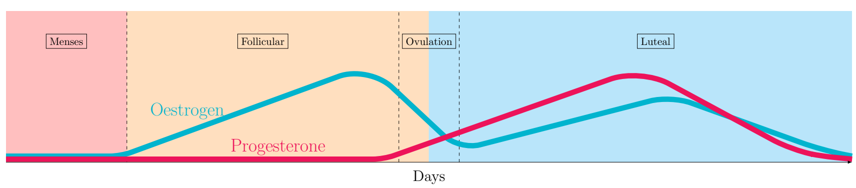

FIGURE 1. Schematic representation of the phases' division and hormonal fluctuations for naturally cycling women.

Power output data are recorded at 1Hz by personal powermeter. An MMP curve is derived from every individual training. Consider an exercise which last T seconds and $Z = \{z_t\}_{1 \leq t \leq T}$ a sequence of observation of the power output. Let $t_1, t_2 \in [\![1, T]\!]$, such that $t_2 - t_1$ is constant, an MMP curve is

$$X(t) = \max_{t_2 - t_1 = t} \frac{z_{t_1} + \cdots + z_{t_2}}{t_2 - t_1}, \quad t = 1, \ldots, T. \tag{1}$$

The data collection lasted from February 2021 to November 2022. Eight high-level female cyclists, with natural cycles, volunteered to participate in the study. To investigate how the menstrual cycle affects the performance of female cyclists, we estimated the different phase of the cycle for each athlete. We asked the cyclists to inform us of the start and end of their period, and we used a robust linear regression model (Soumpasis et al., 2020) to estimate the day of ovulation for each cycle. Their menstrual cycles are then divided into three phases: the menstruation phase, the follicular phase (between the end of the bleeding period and the estimated ovulation day), and the luteal phase (from the estimated ovulation day until the start of the next period). Prior to participation, all the athletes were informed about the purpose of the study. All investigations conformed to the code of ethics of the World Medical Association and were approved by the Institutional

Ethics Committee. Data collection was compliant with the General Data Protection Regulation (2016/679) applied in the European Union.

2 Model

The model is a hierarchical model that takes into account that observations depend on bike types, RPE and athletes and for each athlete we have repeated measurements for each of the three phases (menstrual, follicular and luteal). We assume that the RPE factors and bike type factors are crossed between athletes. This assumption is reasonnable since the factors are independent of the considered athlete. The factors are only partially crossed because we did not observed all the combinations of training intensity and bike type for all athletes. We consider the following model

$$X_{jklmn}(t) = \mu_k(t) + B_{jk}(t) + C_{lk}(t) + D_{mk}(t) + E_{jklmn}(t),\ t \in [\![1, T]\!], \quad (2)$$

where $j = 1, \dots, 8$ (athletes), $k = 1, \dots, 3$ (phases), $l = 0, \dots, 10$ (RPE, Borg-CR10 scale), $m = 1, \dots, 4$ (bike types), $n = 1, \dots, N_{jklm}$ (observations). $X_{jklmn}(t)$ represents the MMP output of the observation n for athlete j during phase k, training intensity l and bike type m for a period of t seconds. $\mu_k(t)$ is the fixed effect for the phase of the menstrual cycle. $B_{jk}(t)$, $C_{lk}(t)$ and $D_{mk}(t)$ are a phase-specific functional random intercept for athletes, for RPE and for bike type respectively. $E_{jklmn}(t)$ is a smooth error term accounting for observation-specific variability. $B_{jk}(t)$, $C_{lk}(t)$, $D_{mk}(t)$ and $E_{jklmn}(t)$ are assumed to be centered and mutually uncorrelated. We allows the covariances of the functional random intercepts to be different for each phase. This assumption is motivated by the intra-phase variation (Figure 2) and by our aim to characterize this variability. The

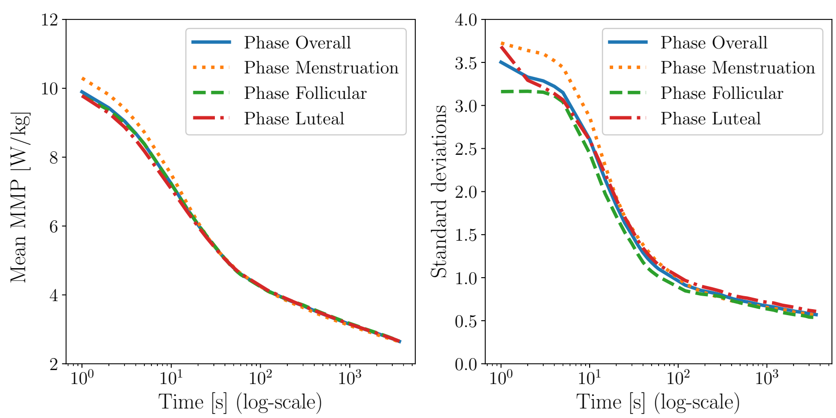

FIGURE 2. Point-wise mean curves (left) and standard deviation curves (right) per phase on a log-scale.

comparison of the fixed effects is performed using bootstrap estimation of the statistics

$$S_N = \frac{N_k N_{k'}}{NT} \|\mu_k - \mu_{k'}\|^2 = \frac{N_k N_{k'}}{NT} \int_{\mathcal{T}} (\mu_k(t) - \mu_{k'}(t))^2 \, \mathrm{d}t, \tag{3}$$

where N, N_k and $N_{k'}$ are the total number of observations, the number of observation for phase k and k' respectively. The sampled bootstrap statistics, under the assumption of equality of the mean curves, are compared to S_N computed on the observed data. The estimation of the composents of the model is performed following Cederbaum (2017).

3 Results

For the comparison of the fixed effects, we generated 5000 bootstrap samples such that there is no difference between phases from the observed data to compare the mean MMP curves of the different phase. For each bootstrap sample, we computed the test statistic (3) for each combination of the cycle phases. Histograms of the resulted test statistics are plotted in Figure 3 with S_N computed on the observed data (plain line) and the 95%-quantile of the distribution of the test statistics computed on the bootstrap samples (dashed line). The test statistic computed on the observed data is smaller than the 95%-quantile of the distribution of the test statistics computed on the bootstrap samples for all phases comparison (Figure 3). There is thus no evidence of a difference between the phases considering their mean MMP curves. We fit the model (2) to all data with μ_k re-

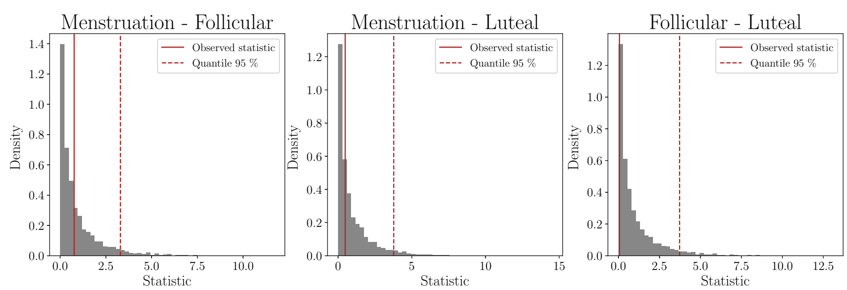

FIGURE 3. Histogram of the test statistic S_N computed on 5000 bootstrap samples. Difference between menstruation and follicular phases (left), menstruation and luteal phases (middle), follicular and luteal phases (right).

placed by a functional random intercept for the phases to obtain the full variance decomposition (Table 1). The curves are standardized and we set the percentage of variance explained to 99.999%. This decomposition highlights the importance of accounting for the different sources of variability as most of the overall variability is induced by the different observations.

TABLE 1. Full variance decomposition for a model with a functional random intercept for phase with pre-specified variance explained of 99.999%.

Variability source	Phase	Athlete	RPE
Variance explained (in %)	2.41×10^{-3}	22.0	11.5
Variability source	Bike type	Observation	Error variance
Variance explained (in %)	16.6	49.8	6.60×10^{-11}

The second most important source of variability is induced by the athletes. It appears that the different phases induce zero variation of power output. Part of the variability in the MMP curves is due to the training intensity (11.5%) and the bike type (16.6%). We have however not proven that there is no variation between phases, we have failed to find evidence of variation between phases. The athletes are thus likely to achieve their peak performance in each phase. These results may be helpful for coaches who use these curves for training planing or the comprehension of their athletes.

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