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A 6-minute sub-maximal run test to predict max

Maximal oxygen uptake ( max) is a key indicator to assess health as well as sports performance. Currently, maximal exercise testing is the most accurate measure of maximal aerobic power, since submaximal approaches are still imprecise. In this paper, we propose a new method to predict max from a submaximal, low intensity, test in sports men and women. 182 males and 108 females from the High Performance Center of Pontevedra (Spain), aged 10-46 years old, with a max between 30.1 and 81.2 mL·min-1·kg-1, completed a maximal incremental test to volitional exhaustion. The test began at a speed of 6 km·h-1 and increased by 0.25 km·h-1 every 15 seconds. Using the data gathered during the first 6 minutes of the test, two different regression models were adjusted using functional data analysis and a traditional linear regression model with scalar covariates. The functional regression model obtained the best results, adjusted r2=0.845 and RMSE=2.8 mL·min-1·kg-1, but the linear regression model also obtained a good fit, adjusted r2=0.798 and RMSE=3.5 mL·min-1·kg-1. Both methods are more accurate than classical submaximal tests, although oxygen consumption needs to be measured during the test.

Abbreviations: =oxygen uptake; =heart rate; RMSE=root mean square error

Keywords: maximum oxygen uptake prediction; low intensity submaximal test

# 1. Introduction

Our understanding of the concept of maximal oxygen uptake and its assessment is rooted in the early work of Hill and Lupton (1923). The assessment of max has widespread utility, from elite athletes to general population (Shepherd, 2009). In heterogeneous, athletic populations, max is indicative of endurance performance capability (Costill et al., 1973) or it can be monitored to assess the efficacy of training interventions (Sartor et al., 2013). As a consequence, max is one of the most frequently measured variables in exercise physiology laboratories (Midgley et al., 2009)

In order to obtain an accurate max, participants must complete an incremental exercise test, either ramp or square wave, to the point of volitional exhaustion (Poole and Jones, 2017). It is recommended, although not universally (Midgley et al., 2008), that a max test last between 8-12 minutes (Poole and Jones, 2017). At the termination of the test, max is determined by a plateau in values (Midgley et al., 2009; Poole and Jones, 2017), or the attainment of secondary criteria indicative of a maximal effort (Duncan et al., 1997). The identification of a plateau and use of secondary criteria is a hotly debated topic (Midgley et al., 2009; Poole and Jones, 2017).

For some populations however, a maximal test is not desirable. In healthy sedentary individuals, maximal testing considerably increases the risk of adverse events (Arena et al., 1997). The risk of adverse cardiovascular events is low in asymptomatic sedentary adults. Maximal tests do however require a high level of motivation to achieve a plateau in , therefore sub-maximal tests are often preferred (Guthrie, 2010). Athletes are recommended to either rest or perform only light exercise the day prior to, and day of testing (Tanner and Gore, 2012). The need to reduce training load prior to testing, along with the potential fatigue from test participation, limit the practicability of regular maximal testing in high-level athletes.

A range of sub-maximal testing protocols have been developed as alternatives to maximal testing, often with the added advantage that they do not require specialist testing equipment. These tests are predictive tests, often associated with high prediction errors (Sartor et al., 2013) and frequently lack movement specificity. However, the variables chosen in predictive models may not be the most appropriate and therefore it is necessary to measure the maximum oxygen consumption during the submaximal test. Another possibility is that the statistical techniques used are too simple, such as simple regression models, and do not allow, among other things, the modelling of complex relationships within the data or to exploit all the information recorded by the monitoring devices.

Functional data analysis is a relatively recent area in the field of statistics and addresses the aforementioned limitations. In a simple way, it can be described as the statistical analysis of data, in which some of its variables are recorded with a high sampling frequency, so observations can be considered as curves that vary in a continuum (Ramsay and Silverman, 2005). For instance, a stress test with respiratory and cardiac variables.

The purpose of this study was to develop a short duration, sub-maximal, treadmill running test to predict max. To facilitate this we planned to compare the use of functional data analysis with more traditional uni and multivariate regression models.

# 2. Material and Methods

## 2.1. Study design

Athletes attending the High Performance Centre in Pontevedra, Spain between 2011 and 2015 completed an incremental test to volitional exhaustion to assess their max. Data from the early stages of the test were used to predict max. This predicted value was then compared to the measured max to determine the accuracy of predicting the final score from sub-maximal data.

## 2.2. Participants

Two hundred and ninety nine participants (182 males and 108 females), aged between 10 and 46 years, completed a max test. They were from a range of sporting disciplines: athletics, badminton, handball, basketball, cycling, football, judo, wrestling, canoeing, rowing, squash, taekwondo, triathlon, and sailing. Table 1 identifies the mean height, mass and age of participants.

All participants were fully informed about the study, and provided written informed consent to participate; this study received institutional ethical approval. For participants under the age of 18, parental consent was provided.

## 2.3. Procedure

Participants were instructed to arrive at the laboratory in a rested, fully hydrated state, at least 3 hours postprandial, having avoided strenuous exercise in the previous 24 hours. On arrival at the laboratory, height and mass were recorded. The max test was conducted as a stand-alone test.

**max test.** After one minute of standing and a 3 minute warm-up at 5 km·h-1, participants completed a max test. The test started at 6 km·h-1 and increased by 0.25 km·h-1 every 15 seconds until volitional exhaustion. Breath by breath gas analysis was recorded throughout the test using Jaegger CPX master screen gas analyser, which was calibrated according to the manufacturer's instructions before each test. max was determined as the attainment of two of the following three criteria *(i)* the attainment of a plateau in *(ii)* respiratory exchange ratio in excess of 1.15 or *(iii)* approximating maximum based 220 - *age*. was measured throughout in mL·min-1·kg-1. was recorded throughout using the i12 lead ECG system that was integrated with the gas analyser.

## Prediction of max

Data from the first 6 minutes of the test were used to predict max. At the end of the 6-minutes period a total distance of 887.5 meters had been covered, the final speed of 12 km·h-1 was, on average, 69.8% (95% CI 69.1, 70.5) of the maximum speed attained at the termination of the test.

The main novelty in the prediction is the use of a regression model with functional data, specifically the model proposed in Müller and Yao (2008), and a linear regression model with non-functional explanatory variables. Functional data analysis (FDA) is a relatively new area in the world of statistics that analyses data which is in continuous nature, for example in a time interval. For more information on the analysis of functional data and its applications consult for example Ramsay and Silverman (2005).

We considered the following explanatory variables: (functional data with information on oxygen consumption per kg weight during the submaximal test), (functional data with heart rate information during submaximal test), (maximum heart rate of the athlete), (average oxygen consumption during sub-maximal test), (maximum oxygen consumption value during submaximal test), (heart rate average during submaximal test), (maximum heart rate value during submaximal test), *age*, *height*, *weight*.

## Statistical analysis

Statistical analysis consisted of adjusting regression models with the maximal oxygen uptake as the dependent variable. For each adjusted model, the explanatory variables that provided a better fit (using the adjusted r2 criterion) were selected, as long as all the variables of the model selected were statistically significant (*P* < 0.05). In practice, max may not always be known, we therefore created models without max and max from different predictive formulae. These predictive formulae were *(i)* the widely used *220 - age* *(ii)* Tanaka et al. (2001) *208 - (0.7 · age)* *(iii)* our own formula based on FDA (Matabuena et al., 2018 under review).

Two different regression models were fitted: the scalar regression model with functional covariates proposed by Müller and Yao (2008), and the classical linear regression model traditionally used in the literature. In the functional additive model all variables were added to the model with additive effects (for more information see (Wood, 2006)).

All statistical analyses were performed using statistical software R and the regression models with functional covariables have been fitted with the fda.usc package (Febrero-Bande and Oviedo de la Fuente, 2012). Figure 1 shows an example of the functional data for in the submaximal test.

# Results

The mean measured max scores were 61.0 ± 7.7 mL·kg-1·min-1 and 55.7 ± 6.8 mL·kg-1·min-1 for males and females respectively. A wide spread of scores is highlighted by the coefficient of variation (12.6% males; 12.2% females) for the measured max.

At the end of the 6-minutes period a total distance of 887.5 meters had been covered, the final speed of 12 km·h-1 was, on average, 69.8% (95% CI 69.1, 70.5) of the maximum speed attained at the termination of the test.

The accuracy of the different models (Table 2) is greater when there is a known value for maximum . Functional analysis resulted in higher r2 values and lower RMSE values. Interestingly, the models that did not use a value for max were stronger than those where max was estimated from popular prediction formulae. Figures 2-5 represent the real vs the fitted values of these regression models.

The formulae of the models that used FDA are not detailed because the mathematical expressions are difficult to calculate without a computer. However, to facilitate the calculation of these expressions, we have developed a web interface through which data such as the age, weight and height of the athlete can be entered, as well as a CSV file containing the submaximal stress test data. This interface (<https://tec.citius.usc.es/mvo2/>) also allows calculation of the other linear regression models, in order to enable comparison with the functional models. Table 3 shows the distribution of the errors of the different models.

# Discussion

The gold standard measurement of max is through the use open circuit spirometry. Tanner and Gore (2012) reported the test - re-test error when using this approach to be 2-3%, while Winter et al (2007) reported the 95% limits of agreement to be ± 2 mL·min-1·kg-1. Our RMSE in the model using functional data analysis that included the maximum is 2.80 mL·min-1·kg-1 which is extremely close to these values. Furthermore, it is lower than values typically reported for sub-maximal predictions from treadmill tests, which tend to be between approximately 4 - 6 mL·min-1·kg-1 (Foster et al., 1996; Mier and Gibson, 2004).

In this paper, max was accurately predicted from the data gathered during the first 6 minutes of an incremental protocol to exhaustion. The protocol employed a small increase in speed every 15 s, requiring expired gas and to be collected. Our prediction only used data from these two variables recorded during the early stages of the test, where 95% of participants were below 70.5% of their maximum final test speed. Functional data techniques were the most accurate therefore demonstrating it to be a powerful tool; considerably superior to the accuracy of the simple regression models used up to now in literature. This high level of accuracy was achieved using a large, heterogeneous sample of sportsmen and women ( max range: 30.2 and 80.1 mL·min-1·kg-1; mass range: 35.2 and 132.0 kg).

The application of functional data techniques to data sampled frequently by automated equipment is becoming increasingly popular. Generally, through these statistical techniques it is possible to achieve a greater level of accuracy in prediction while reducing the variance in the estimated parameters and still preserving statistical significance in the different statistical models fitted. However, large sample sizes are required to use applied functional data techniques. This is an important limitation for many studies. In this study, the use of techniques based on functional data involved obtaining recordings of and throughout the initial stages of the test. These data are required so that a curve showing the evolution of these variables throughout the test can be constructed. Introducing this information into the model in the form of a curve means considering each observation as an independent variable. This is the most likely reason for the increased accuracy of the functional model compared to the classical models in this specific problem.

The accuracy of the simple models of regression was surprisingly good and the simple formulae can be interpreted in a useful way from a clinical and physiological point of view. Surprisingly, when using the stepwise method of entering variables into the simple linear regression, the variable did not provide the most accurate prediction. Instead both the mean () and maximum () during the first 6 minutes of the test had the highest predictive power. The most likely explanation is that the point where the maximal test is terminated, each participant has attained their maximum . In heterogeneous samples, the correlation between and is often low because for the same , aerobically fitter individuals have a higher (Strath et al. 2002). It is therefore likely that between individuals of a similar age there is a relatively small variation in max, but a considerably larger inter-individual variation in max. The max is therefore a better predictor of the endpoint of the test than the .

The inclusion of the maximum heart rate in both the linear model and the functional model dramatically increased the prediction accuracy in this study; the RMSE was reduced by over 25%. Where maximum is known, our new method provides an accurate prediction of max. However, where an individual's max is unknown, practitioners have a dilemma; either determine maximal or estimate it from formulae that tend to be inaccurate (Matabuena et al under review). We found that including an estimated max using either Tanaka et al. (2001) formula (208 - 0.7 · *age*) or (220 - *age*) gave RMSE of 4.2 and 4.5 mL·min-1·kg-1 respectively. These values are worse than when no value for max is used. Initially, this may seem counterintuitive, however given the predictive errors associated with these formulae it is not entirely surprising. Applying FDA to our data, we derived a prediction for max (see Matabuena et al in review for full details); max derived from this method and then used in the prediction of max, reduced the RMSE to 3.4 mL·min-1·kg-1.

In a clinical setting, sub-maximal cycle ergometer tests are considered to be the gold standard mode of testing (Sartor et al., 2013) despite their lack of movement specificity. Sartor et al. (2013) also report extensive use of cycle ergometry based testing in both healthy and athletic populations. The mode of exercise testing is important because lower max scores are typically recorded in cycle ergometer tests than treadmill tests (Glassford et al., 2000; Harrison et al., 1980). These lower scores could potentially lead to a misdiagnosis or incorrect categorisation of an individual. An accurate sub-maximal running based test therefore has wide applicability to many settings. On this basis, our sub-maximal treadmill test has the potential to provide a more valid prediction of cardiovascular function, with a low predictive error.

Maximal tests are considered inappropriate for the general population (Noonan and Dean, 2000). Sub-maximal tests are therefore frequently used in tests on sedentary and clinical populations. Moreover, a low level of pre-operative cardiovascular fitness is associated with increased post-operative complications (Tew et al., 2014). A more accurate sub-maximal test will aid practitioners in the diagnosis and categorisation of patients. Patients with cardiovascular disease often display slowed on-kinetics for oxygen uptake, which can affect predicted max scores (Arena et al 2007). In this test oxygen uptake was measured throughout, however further research is required on these populations to validate the test. In addition, the starting speed of this test would preclude its use with some elderly and clinical groups. Whether this test could be modified for their use is yet to be determined.

In 18% of our sample, the prediction error was higher than 4 mL·min-1·kg-1. This level of error means that caution should be applied, albeit in a small proportion of the sample, when interpreting the data, particularly when categorising individuals. An important aspect in the analysis of the errors is the relationship between the relative intensity reached by the athlete at 6 minutes and the residuals in the predicted model (Figure 6). A test of independence between these two variables was significant (*P* < 0.001) therefore rejecting the hypothesis of independence. A close examination of Figure 6, highlights a degree of dependence, but it is only weak, appearing for particularly low or high intensity values. To overcome this, future research could examine adjusting the start speed based on an estimated level of fitness, or terminating the test at the same relative point, for example ventilatory threshold. The practicability of these suggestions remains to be established.

While this test is a useful development, it does require the use of open circuit spirometry. This requirement reduces the overall utility of the test compared to other tests that only require only e.g. ACSM test (Marsh, 2012) or the stage of the test reached e.g. Bruce test (Bruce et al., 1973). However, this test has a lower prediction error than other similar tests and therefore represents a valuable new approach for practitioners.

# Conclusions

In this study, a new methodology for the prediction of maximum oxygen consumption has been presented. It combines a relatively low level of effort, during a 6 minutes sub-maximal exercise test, with functional data analysis. Despite the brevity of the test and low level of exercise required the test provides an accurate prediction of max in a large, healthy, heterogeneous population.

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# Tables and graphics

Table 1. Participant characteristics.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **182 Men** | | | | | |
|  | **Min** | **Max** |  |  |  |
| **Age** | 13.00 | 46.00 | 18.71 | 17.00 | 5.79 |
| **Weight (kg)** | 35.20 | 132.00 | 72.19 | 70.65 | 12.18 |
| **Height (cm)** | 149.50 | 194.00 | 176.18 | 176.00 | 6.94 |
|  | 2.07 | 6.56 | 4.37 | 4.35 | 0.65 |
|  | 30.20 | 81.10 | 60.96 | 61.50 | 7.71 |
|  | 175.00 | 218.00 | 196.52 | 197.00 | 9.01 |
| **108 Women** | | | | | |
|  | **Min** | **Max** |  |  |  |
| **Age** | 13.00 | 44.00 | 17.47 | 16.00 | 4.39 |
| **Weight (kg)** | 41.90 | 81.10 | 57.68 | 58.05 | 6.55 |
| **Height (cm)** | 151.50 | 189.00 | 165.51 | 164.45 | 6.54 |
|  | 2.20 | 4.17 | 3.20 | 3.18 | 0.47 |
|  | 44.50 | 77.10 | 55.71 | 55.45 | 6.77 |
|  | 175.00 | 215.00 | 196.64 | 197.00 | 8.59 |

MHR = maximun HR; = mean; = median; = standard deviation.

Table 2. Goodness-of-fit of the linear and functional regressions for the dataset considered in this study.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Regression** | **MHR** |  | **r2  adjusted** | **RMSE** | **ME** |
| Linear | Y | -20.233706 + 0.1348 *· height* - 0.094258 *· weight* + 1.172685 *·*  + 0.424026 *· MHR* + 0.12408 *·*  - 0.517517 *·* | 0.80 | 3.5 | 11.4 |
| Linear | N | 23.453697 + 0.179609 *·* *height* - 0.118106 *·* *weight* + 1.312513 *·*  + 0.107467 *·*  - 0.339127 *·* | 0.67 | 4.4 | 14.0 |
| Functional | Y | s() + s(*HR*) + s(*height*) + s(*weight*) + s(*MHR*) | 0.85 | 2.8 | 7.3 |
| Functional | N | s() + s(*HR*) + s(*height*) + s(*weight*) | 0.76 | 3.5 | 9.3 |

MHR = maximun HR; RMSE = root-mean-square deviation; ME = maximun error; = maximun oxygen consumption per kg in the first six minutes of the stress test; = average heart rate in the first six minutes of the stress test; = maximun heart rate in the first six minutes of the stress test; and $s$ denotes an additive effect over functional data.

Table 3. Distribution of residuals for measured versus predicted max (mL *·* kg-1 *·* min-1). Each column represents a range of residuals scores and the value in the table is the number of participants in that range

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Regression** | **MHR** | **(-16,-12]** | **(-12,-8]** | **(-8,-4]** | **(-4,0]** | **(0,4]** | **(4,8]** | **(8,12]** | **(12,16]** |
| Linear | Y | 0 | 3 | 35 | 115 | 94 | 39 | 4 | 0 |
| Linear | N | 0 | 8 | 47 | 97 | 84 | 41 | 12 | 1 |
| Functional | Y | 0 | 0 | 19 | 129 | 109 | 33 | 0 | 0 |
| Functional | N | 0 | 1 | 40 | 105 | 103 | 37 | 4 | 0 |

MHR = maximun HR

consumo

Figure 1. Oxygen consumption per kg in the first six minutes of the stress test.

Figure 2. Measured versus predicted values for linear regression model using known value of *HR* max.

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Figure 3. Measured versus predicted values for functional regression model using known value of *HR* max.

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Figure 5. Measured versus predicted values for functional regression model using no value for *HR* max.

Figure 4. Measured versus predicted values for linear regression model using no value for *HR* max.

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Figure 6. % intensity reached in the submaximal test vs residuals for functional regression model using known value of *HR* max.