

# shorts: An R Package for Modeling Short Sprints

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## ABSTRACT

Short sprint performance is one of the most distinguishable and admired physical traits in sports. Short sprints have been modeled using the mono-exponential equation that involves two parameters: (1) maximum sprinting speed (MSS) and (2) relative acceleration (TAU). The most common methods to assess short sprint performance are with a radar gun or timing gates. In this paper, we: 1) provide the **shorts** package that can model sprint timing data from these two sources; 2) discuss potential issues with assessing sprint time (synchronization and flying start, respectively); and 3) provide model definitions within the **shorts** package to help alleviate errors within the subsequent parameter outcomes.

## 1 INTRODUCTION

Short sprint performance is one of the most distinguishable and admired physical traits in sports. Short sprints, commonly performed in most team sports (e.g., soccer, field hockey, handball, football, etc.), are defined as maximal running from a stand still position over a distance that doesn't result in deceleration at the end. Peak anaerobic power is achieved within the first few seconds ( $<5$  s) of maximal efforts (Mangine et al. 2014), whereas the ability to achieve maximal sprint speed varies based on the type of sport. For example, track and field sprinters are trained to achieve maximal speed later in a race (i.e., 50-60 m) (Ward-Smith 2001), but team sport athletes have sport-specific attributes and reach it much sooner (i.e., 30-40 m) (Brown, Vescovi, and Vanheest 2004). Regardless of the differences in kinematics between athletes, evaluating short sprint performance is routinely included within a battery of fitness tests for a wide range of sports.

The use of force plates is considered the gold standard for assessing mechanical properties of sprinting; however, there are logistical and financial challenges to capturing the profile of an entire sprint (Jean-Benoit Morin et al. 2019; Samozino et al. 2016). Radar and laser technology are frequently used laboratory-grade methods (Buchheit et al. 2014; Edwards et al. 2020; Jiménez-Reyes et al. 2018; Marcote-Pequeño et al. 2019) but not normally accessible to practitioners working in sports. Undoubtedly, the most common method available and used to evaluate sprint performance are timing gates. Often multiple gates are positioned at varying distances to capture split times (e.g., 5, 10, 20 m), which can now be incorporated into the method for determining sprint mechanical properties (Jean-Benoit Morin et al. 2019; Samozino et al. 2016). This approach presents an advantage to practitioners who can use the outcomes to describe individual differences, quantify the effects of training interventions, and better understanding the limiting factors of performance.

The **shorts** package (Jovanovic 2020), written in the R language (R Core Team 2020), represents an open-source tool to help sport scientists translate raw timing data into detailed mechanical outcomes through mathematical modeling (Jean-Benoit Morin et al. 2019; Samozino et al. 2016). To best of our knowledge, scientist, researchers, and coaches have been performing short sprints modeling using the built-in solver function of Excel (Microsoft Corporation, Redmond, Washington, United States) (J. B. Morin 2017; Jean-Benoit Morin and Samozino 2019; Stenroth, Vartiainen, and Karjalainen 2020; Stenroth

and Vartiainen 2020; Samozino et al. 2016; Clark et al. 2017; Jean-Benoit Morin et al. 2019), which makes the **shorts** package major improvement in ease-of-use, speed, transparency, reproducibility, and more feature-rich model fitting.

In the current paper, we will provide an explanation of one commonly used mathematical equation to model short sprints, modeling applications using the **shorts** package, issues that can arise during measurement and estimation, and potential solutions to those problems.

## 2 MATHEMATICAL MODEL

Short sprints have been modeled using the mono-exponential equation (1) originally proposed by Furu-sawa, Hill, and Parkinson (1927), and more recently popularized by Clark et al. (2017), and Samozino et al. (2016). Equation (1) represents function for instantaneous horizontal velocity  $v$  given the time  $t$  and two model parameters:

$$v(t) = MSS \times (1 - e^{-\frac{t}{TAU}}) \quad (1)$$

The parameters of the equation (1) are *maximum sprinting speed* (MSS; expressed in  $ms^{-1}$ ) and *relative acceleration* (TAU). Mathematically, TAU represents the ratio of MSS to initial acceleration (MAC; *maximal acceleration*, expressed in  $ms^{-2}$ ) (2).

$$MAC = \frac{MSS}{TAU} \quad (2)$$

Although TAU is used in the equations, and later estimated, it is preferred to use MAC instead since it is easier to grasp, particularly for less math inclined coaches.

By derivating equation (1), we can get equation for horizontal acceleration (3).

$$a(t) = \frac{MSS}{TAU} \times e^{-\frac{t}{TAU}} \quad (3)$$

By integrating equation (1), we can get equation for distance covered (4).

$$d(t) = MSS \times (t + TAU \times e^{-\frac{t}{TAU}}) - MSS \times TAU \quad (4)$$

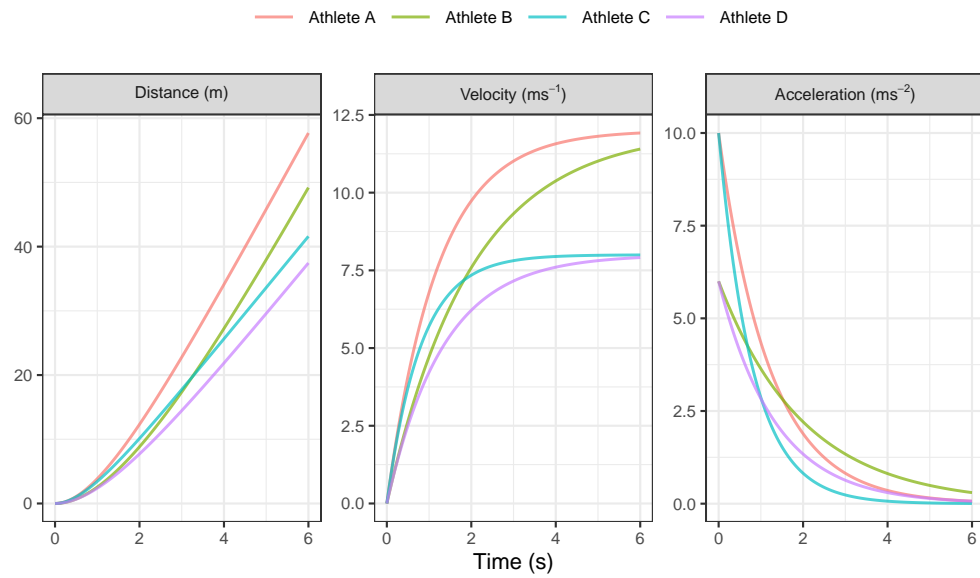
Let's consider four athletes with different levels of MSS (high versus low maximal sprinting speed) and MAC (high versus low maximal acceleration; as mentioned previously, using MAC is preferred over using TAU) (Table 1).

Figure 1 depicts distance, velocity, and acceleration over time (from 0 to 6 s).

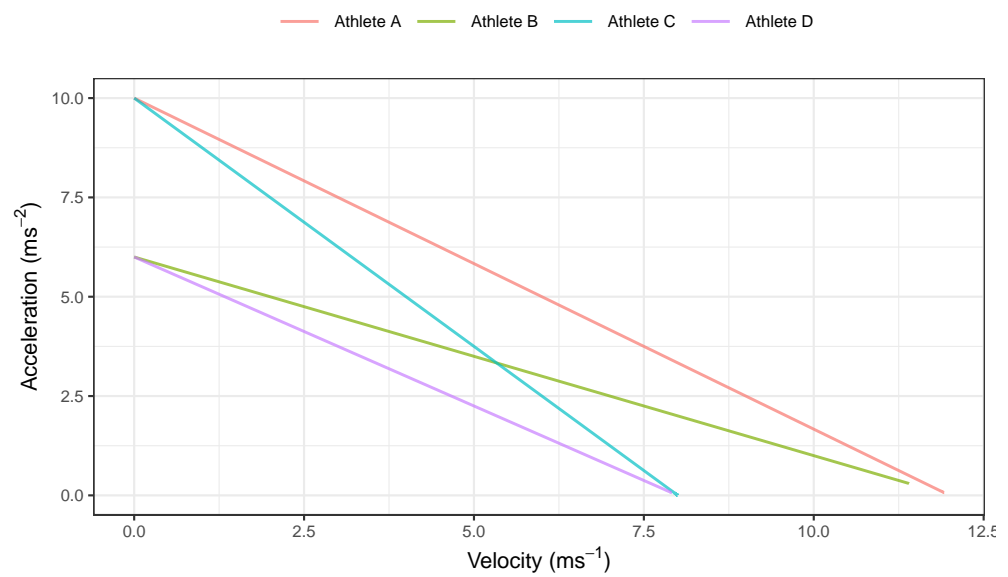
Plotting acceleration against velocity (Figure 2), we will get *Acceleration-Velocity Profile*, which is linear, according to the mathematical model. If the athlete's body mass (kg) is known, as well as additional air resistance parameters (see Air resistance and the calculation of force and mechanical power section of this paper), *Force-Velocity Profile* can be estimated (see Force-Velocity profile section of this paper).

**Table 1.** Four athletes with different MSS and MAC parameters.

Athlete	MSS	MAC	TAU
Athlete A	12	10	1.20
Athlete B	12	6	2.00
Athlete C	8	10	0.80
Athlete D	8	6	1.33



**Figure 1.** Kinematic characteristic of four athletes with different MSS and MAC parameters over a period of 0 to 6 seconds.



**Figure 2.** Acceleration-Velocity profile of four athletes with different MSS and MAC parameters.

### 72 3 ESTIMATION USING SHORTS PACKAGE

73 Short sprints profiling is usually performed by: (1) measuring split times using timing gates (i.e., positioned  
74 at various distances, e.g., 5, 10, 20, 30, 40 m), (2) getting a velocity trace using a radar gun. Estimation  
75 of MSS and TAU parameters from equation (1) is performed in **shorts** package using non-linear least  
76 squares regression implemented in the `nls()` function in the **base R** (R Core Team 2020) and `nlme()`  
77 function in the **nlme** package (Pinheiro, Bates, and R-core 2020) for the mixed-effect models.

#### 78 3.1 Estimating short sprint parameters using split times

79 Let's consider an example of an athlete with MSS equal to  $9\text{ ms}^{-1}$ , TAU equal to 1.3, and MAC equal to  
80  $6.92\text{ ms}^{-2}$  performing 40m sprint with timing gates positioned at each 10m split. For split times, distance  
81 is a predictor, and time is the outcome variable, thus the equation (1) becomes:

$$t(d) = TAU \times W(-e^{\frac{-d}{MSS \times TAU}} - 1) + \frac{d}{MSS} + TAU \quad (5)$$

82  $W$  in equation (5) represents Lambert's W function (Goerg 2020). MSS and TAU parameters are  
83 estimated using `model_using_splits()` function:

```
require(shorts)

split_distance <- c(10, 20, 30, 40)

split_time <- c(2.17, 3.43, 4.60, 5.73)

m1 <- model_using_splits(
  distance = split_distance,
  time = split_time
)

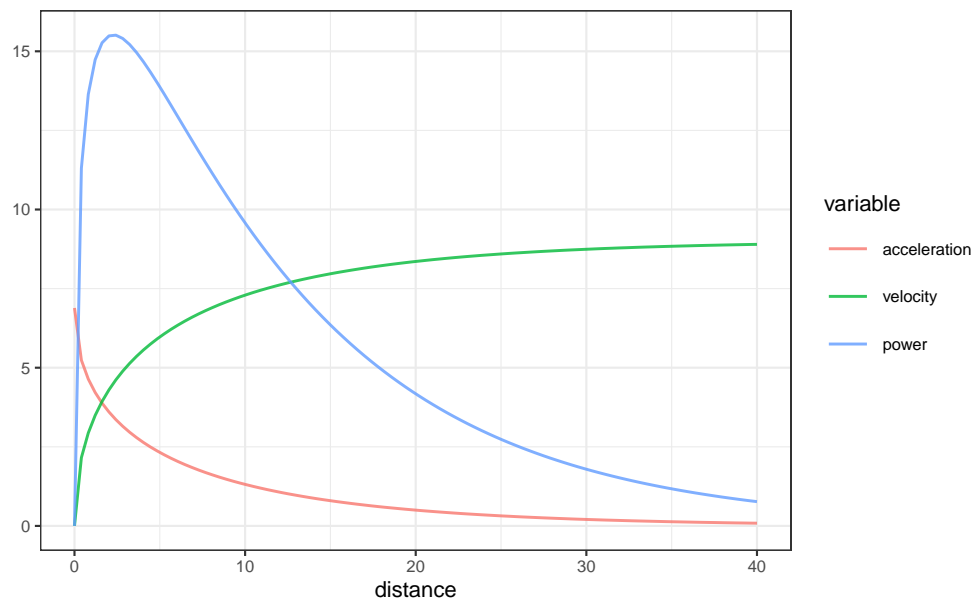
m1
#> Estimated model parameters
#> -----
#>               MSS               TAU               MAC
#>               9.01               1.31               6.89
#>          PMAX    time_correction distance_correction
#>          15.52             0.00             0.00
#>
#> Model fit estimators
#> -----
#>          RSE R_squared    minErr    maxErr maxAbsErr    RMSE
#>    0.00249    1.00000   -0.00178    0.00265    0.00265    0.00176
#>          MAE          MAPE
#>    0.00157    0.04742
```

84 Maximal relative power (PMAX) from the output is estimated using  $\frac{MSS \times MAC}{4}$ , which disregards the  
85 air resistance. `time_correction` and `distance_correction` parameters will be covered later in  
86 the paper.

87 Besides providing *residual standard error* (RSE), **shorts** functions provide additional model fit  
88 estimators. Additional information can be gained by exploring the returned object, particularly object  
89 returned from the `nls()` function (i.e., by using the `S3 summary()` method). To extract estimated  
90 model parameters, use `S3 coef()` method.

91 To create a simple plot of the model, use `S3 plot()` method, which returns **ggplot2** (Wickham,  
92 Chang, et al. 2020) object:

```
plot(m1) + theme_bw(8)
```



93

94 Once we have estimated MSS and TAU, we can use `predict_XXX()` family of functions to predict  
95 various relationships (i.e., time at distance, acceleration at distance, velocity at time, etc.):

```
# Predict time at distance
predict_time_at_distance(
  distance = split_distance,
  MSS = m1$parameters$MSS,
  TAU = m1$parameters$TAU
)
#> [1] 2.17 3.43 4.60 5.73
```

### 96 3.1.1 Air resistance and the calculation of force and mechanical power

97 To estimate force production at distance or time (using `predict_force_at_distance()` and `pre-`  
98 `dict_force_at_time()` functions), as well as power production (using `predict_power_at-`  
99 `distance()` and `predict_power_at_time()` functions), one needs to take into account the air  
100 resistance. Air resistance (N) is estimated using `get_air_resistance()` function, which takes  
101 velocity, body mass (kg), body height (m), barometric pressure (Torr), air temperature ( $^{\circ}\text{C}$ ), and wind  
102 velocity ( $\text{ms}^{-1}$ ) as parameters (please refer to Arsac and Locatelli (2002), Samozino et al. (2016), and  
103 van Ingen Schenau, Jacobs, and de Koning (1991) for more information):

```
get_air_resistance(
  velocity = 5,
  bodymass = 80,
  bodyheight = 1.85,
  barometric_pressure = 780,
  air_temperature = 20,
  wind_velocity = 0.5
)
#> [1] 6.1
```

104 When estimating force and power, the air resistance parameters can be set using "...", which are  
105 forwarded to the `get_air_resistance()`:

```

# To calculate horizontal force produced
predict_force_at_distance(
  distance = split_distance,
  MSS = m1$parameters$MSS,
  TAU = m1$parameters$TAU,
  # Additional parameters forwarded to get_air_resistance
  # Otherwise, defaults are used
  bodymass = 80,
  bodyheight = 1.85,
  barometric_pressure = 780,
  air_temperature = 20,
  wind_velocity = 0.5
)
#> [1] 119.0 58.6 36.9 28.2

```

106     The easiest way to get all kinematics and kinetics for short sprints is to use `predict_kinemat-`  
 107 `ics()` function:

```

df <- predict_kinematics(
  m1,
  max_time = 6,
  frequency = 100,
  # Additional parameters forwarded to get_air_resistance
  # Otherwise, defaults are used
  bodymass = 80,
  bodyheight = 1.85,
  barometric_pressure = 780,
  air_temperature = 20,
  wind_velocity = 0.5
)

```

108     Plotting the model predictions can be done once we convert data from wide to long with the help of  
 109 **ggplot2** (Wickham, Chang, et al. 2020), **dplyr** (Wickham, François, et al. 2020), **tidyr** (Wickham 2020),  
 110 and **tidyverse** (Wickham 2019) packages:

```

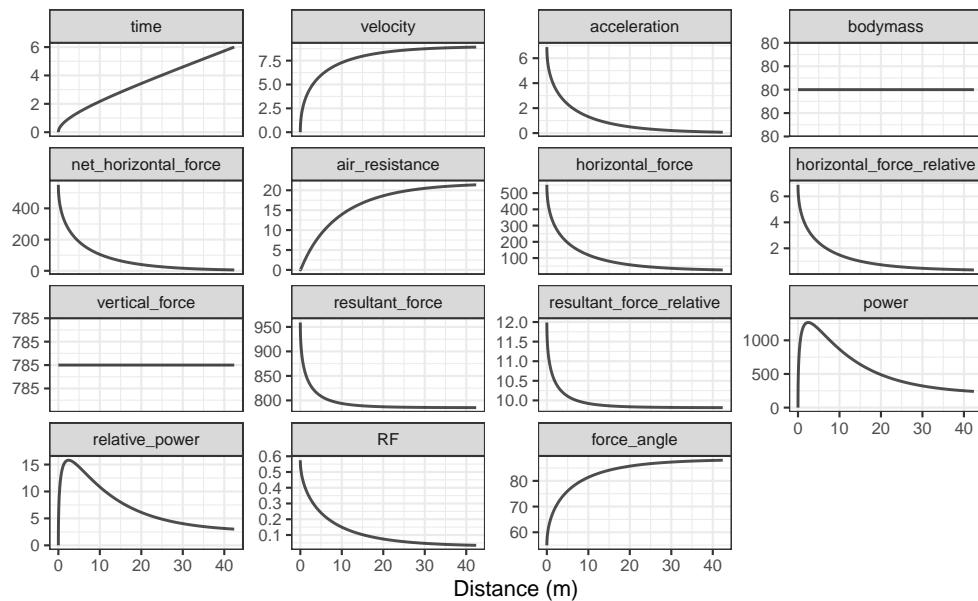
require(tidyverse)

variable_names <- colnames(df)

df <- pivot_longer(data = df, cols = -2) %>%
  mutate(name = factor(name, levels = variable_names))

ggplot(df, aes(x = distance, y = value)) +
  theme_bw(8) +
  facet_wrap(~name, scales = "free_y") +
  geom_line(alpha = 0.7) +
  ylab(NULL) +
  xlab("Distance (m)")

```



111

112 These kinematic and kinetic variables are utilized in Force-Velocity profile estimation, which is  
 113 covered later in this paper.

### 114 3.1.2 Utility functions

115 Another valuable addition for sport scientists and coaches is the ability to determine the distances and  
 116 times where 90% of maximum sprinting speed is reached, or where peak power is within 90% range. To  
 117 identify these values, **shorts** package comes with `find.XXX()` family of functions:

```
# Finds distance where 90% of maximum sprinting speed is reached
find.velocity_critical.distance(
  MSS = m1$parameters$MSS,
  TAU = m1$parameters$TAU,
  percent = 0.9
)
#> [1] 16.5

# Finds maximal power and distance (this time using air resistance)
find.max.power.distance(
  MSS = m1$parameters$MSS,
  TAU = m1$parameters$TAU,
  # Additional parameters forwarded to get_air_resistance
  # Otherwise, defaults are used
  bodymass = 80,
  bodyheight = 1.85,
  barometric.pressure = 780,
  air.temperature = 20,
  wind.velocity = 0.5
)
#> $max.power
#> [1] 1264
#>
#> $distance
#> [1] 2.46

# Finds distance over 90% power range
find.power_critical.distance(
```

```

MSS = m1$parameters$MSS,
TAU = m1$parameters$TAU,
# Additional parameters forwarded to get_air_resistance
# Otherwise, defaults are used
bodymass = 80,
bodyheight = 1.85,
barometric.pressure = 780,
air.temperature = 20,
wind.velocity = 0.5
)
#> $lower
#> [1] 0.959
#>
#> $upper
#> [1] 5.44

```

### 118 3.1.3 Mixed-effects model

119 Sprint performance is often evaluated with a group of athletes (e.g., soccer club) representing a single  
120 strata of interest. Sports scientists can estimate individual profiles, or utilize mixed-effects models. To  
121 perform mixed-effects models in **shorts** for split times, one can use `mixed_model_using_splits()`  
122 function. To demonstrate this functionality, we load the `split_times` dataset provided in the **shorts**  
123 package:

```

data(split_times)

# Mixed model
m2 <- mixed_model_using_splits(
  data = split_times,
  distance = "distance",
  time = "time",
  athlete = "athlete",

  # Select random effects
  # Default is MSS and TAU
  random = MSS + TAU ~ 1
)

m2
#> Estimated fixed model parameters
#> -----
#>               MSS               TAU               MAC
#>             8.065             0.655             12.309
#>             PMAX   time_correction distance_correction
#>             24.818             0.000             0.000
#>
#> Estimated random model parameters
#> -----
#>   athlete  MSS   TAU   MAC  PMAX  time_correction
#> 1   James  9.69 0.847 11.4 27.7              0
#> 2    Jim   7.83 0.505 15.5 30.4              0
#> 3   John   7.78 0.727 10.7 20.8              0
#> 4 Kimberley 8.57 0.802 10.7 22.9              0
#> 5 Samantha 6.45 0.395 16.3 26.4              0
#> distance_correction
#> 1              0

```



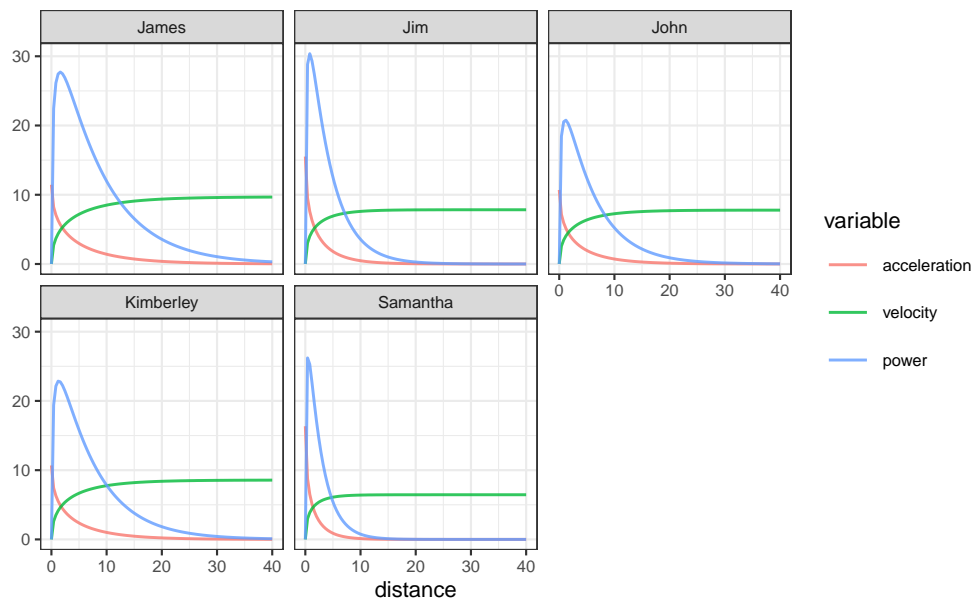
```

#> 2 0
#> 3 0
#> 4 0
#> 5 0
#>
#> Model fit estimators
#> -----
#>      RSE R_squared minErr maxErr maxAbsErr RMSE
#> 0.0260 0.9998 -0.0293 0.0496 0.0496 0.0214
#>      MAE MAPE
#> 0.0172 0.9019

```

124 Additional information about mixed-effects model performed using the `nlme` package (Pinheiro,  
 125 Bates, and R-core 2020) can be obtained using `summary()` function. S3 method `coef()` when applied  
 126 on mixed-model result will return both the fixed and random effects. To create a simple plot of the model,  
 127 use S3 `plot()` method.

```
plot(m2) + theme_bw(8)
```



128

129 The following figure contains kinematics for all athletes in `split_times` dataset. Please note that  
 130 power calculation takes default parameters for each individual:

```

df <- predict_kinematics(m2, max_time = 10)

variable_names <- colnames(df)

df <- pivot_longer(df, cols = c(-1, -3)) %>%
  mutate(name = factor(name, levels = variable_names))

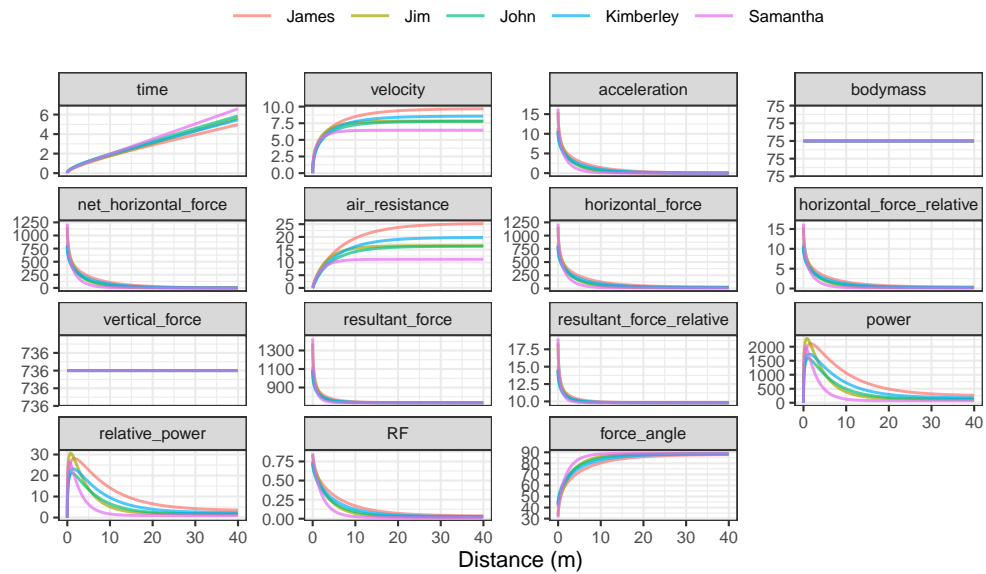
ggplot(
  filter(df, distance < 40),
  aes(x = distance, y = value, group = athlete, color = athlete)
) +
  theme_bw(8) +
  facet_wrap(~name, scales = "free_y") +

```

```

geom_line(alpha = 0.7) +
ylab(NULL) +
xlab("Distance (m)") +
theme (
  legend.position = "top",
  legend.title = element_blank()
)

```



131

### 3.2 Estimating short sprint parameters using radar gun

132

133 Estimation of the short sprint profile using radar gun data takes time as predictor and velocity as the  
 134 outcome variable. Thus equation (1) is used to estimate MSS and TAU.

135 Let's consider the same example of an athlete with MSS equal to  $9 \text{ ms}^{-1}$ , TAU equal to 1.3, and MAC  
 136 equal to  $6.92 \text{ ms}^{-2}$  performing 40m sprint with velocity estimated using radar run (in this case with 1 Hz  
 137 sampling rate).

```

sprint_time <- seq(0, 6, 1)

sprint_velocity <- c(0.00, 4.83, 7.07, 8.10, 8.59, 8.81, 8.91)

m3 <- model_using_radar(
  velocity = sprint_velocity,
  time = sprint_time
)

```

138 Both split and radar gun models allow the use of *weighted* non-linear regression. For example, we can  
 139 give more weight to shorter distance or faster velocities. Weighted non-linear regression is performed by  
 140 setting weights parameter:

```

m3.weighted <- model_using_radar(
  velocity = sprint_velocity,
  time = sprint_time,
  weights = 1 / (sprint_velocity + 1)
)

```

### 141 3.2.1 Mixed-effects model

142 Mixed-effects model using radar data is done using `mixed_model_using_radar()` function. To  
143 perform mixed model, let's load data that comes with **shorts** package.

```
data("radar_gun_data")

m4 <- mixed_model_using_radar(
  radar_gun_data,
  time = "time",
  velocity = "velocity",
  athlete = "athlete"
)
```

### 144 3.3 Force-Velocity profile

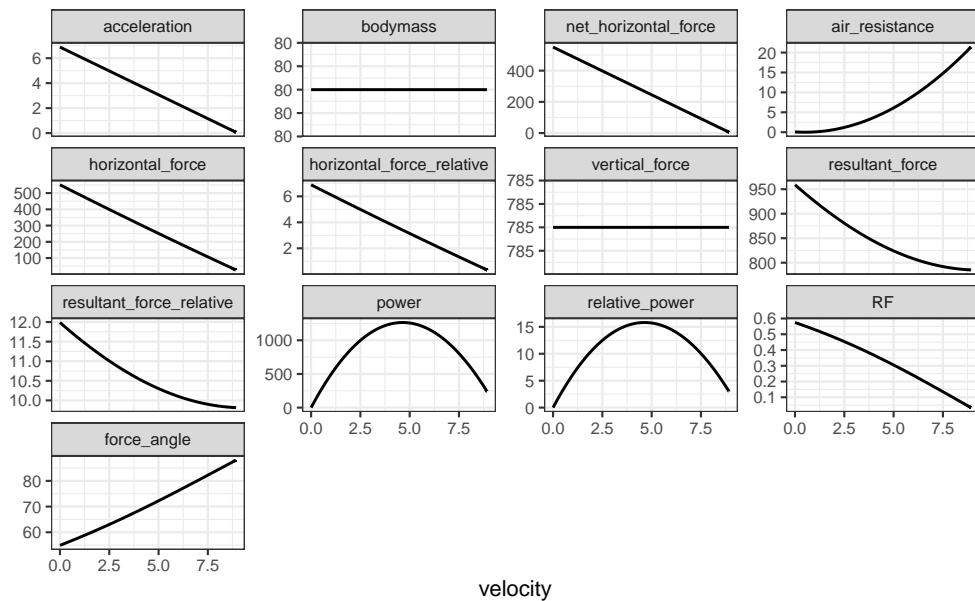
145 To create *Force-Velocity Profile* (FVP) using single athlete estimated sprint model parameters (i.e., TAU  
146 and MSS), you can use `get_FV_profile()` function. When estimating FVP, athlete body mass (kg)  
147 can be set using `bodymass` parameter, while the air resistance parameters can be set using "...", which  
148 are forwarded to the `get_air_resistance()` function. Details of the FVP method implemented  
149 in the **shorts** package, as well as the interpretation from a sprint training perspective, are covered  
150 elsewhere (Thomas A. Haugen, Breitschädel, and Samozino 2020; Jean-Benoit Morin and Samozino  
151 2016; Jean-Benoit Morin et al. 2019; Samozino et al. 2016).

```
# To create Force-Velocity Profile
fvp <- get_FV_profile(
  MSS = m1$parameters$MSS,
  TAU = m1$parameters$TAU,
  bodymass = 80,
  # Additional parameters forwarded to get_air_resistance
  # Otherwise, defaults are used
  bodyheight = 1.85,
  barometric_pressure = 780,
  air_temperature = 20,
  wind_velocity = 0.5
)

fvp
#> Estimated Force-Velocity Profile
#> -----
#>      bodymass      F0      F0_rel      V0
#>      80.00000    544.51032    6.80638    9.36184
#>      Pmax Pmax_relative    FV_slope    RFmax_cutoff
#>    1274.40402    15.93005    -0.72703    0.30000
#>      RFmax      Drf      RSE_FV      RSE_Drf
#>      0.48779    -0.06676    1.54814    0.00447
```

152 To plot FVP kinematics and kinetics (which are exactly the same as generated by the `predict_-`  
153 `kinematics()` function), use `S3 plot()` function. By default, FVP estimated kinetics are plotted  
154 against velocity (on x-axis).

```
plot(fvp) + theme_bw(8)
```



155

156 To plot FVP estimated kinetics against time, use `type = "time"` parameter:

```
plot(fvp, "time") + theme_bw(8)
```

## 157 4 PROBLEMS WITH ESTIMATION

158 There is a challenge when collecting sprint data that could have a substantial impact on modeled outcomes.  
 159 To ensure accurate parameter outcomes, the initial force production must be synced with start time  
 160 (Thomas A. Haugen, Breitschädel, and Samozino 2020; Thomas A. Haugen, Breitschädel, and Seiler  
 161 2019). Below we describe this challenge when using radar guns or timing gates and suggest potential  
 162 solutions within the **shorts** package.

### 163 4.1 Problems with time sync with radar gun

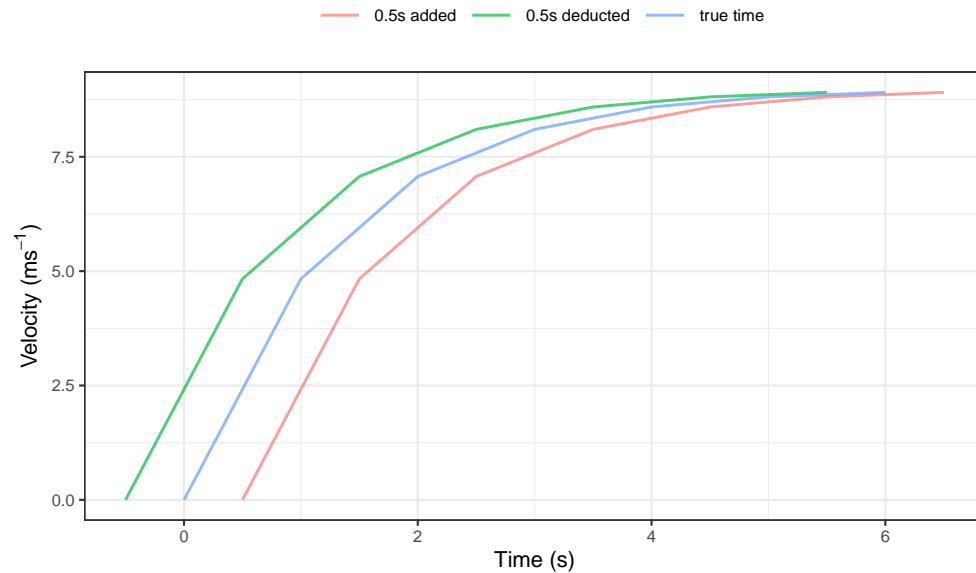
164 One source of error in the modeled estimation using a radar gun is the time synchronization. In theory,  
 165 synchronization is ideal when a sprint is initiated at  $t = 0$  (i.e.,  $v(t = 0) = 0$ ). In practice, this is often not  
 166 the case. Let's use our athlete and add and deduct 0.5 s to simulate an error in synchronization and its  
 167 effect on estimated MSS and TAU.

```
df <- tibble(
  `true time` = sprint_time,
  velocity = sprint_velocity,
  `0.5s added` = `true time` + 0.5,
  `0.5s deducted` = `true time` - 0.5
)

plot_df <- pivot_longer(df, cols = -2, names_to = "Sync issue")

ggplot(
  plot_df,
  aes(x = value, y = velocity, color = `Sync issue`)
) +
  theme_bw(8) +
  geom_line(alpha = 0.7) +
  xlab("Time (s)") +
  ylab(expression("Velocity (" * ms^-1 * ")")) +
```

```
theme (
  legend.title = element_blank(),
  legend.position = "top"
)
```



168

169 The following three models estimate MSS and TAU from the three datasets. Tables are created  
 170 using the `kable()` function from the **knitr** package (Xie 2014, 2015, 2020) and `kable_styling()`  
 171 function from the **kableExtra** package (Zhu 2021).

```
require(knitr)
require(kableExtra)

# Without synchronization issues
m5 <- model_using_radar(
  velocity = df$velocity,
  time = df$`true time`
)

# With time added
m6 <- model_using_radar(
  velocity = df$velocity,
  time = df$`0.5s added`
)

# With time deducted
m7 <- model_using_radar(
  velocity = df$velocity,
  time = df$`0.5s deducted`
)

model_df <- rbind(
  data.frame(
    model = "True time",
    t(coef(m5))
  ),

```

```

data.frame(
  model = "Added 0.5s time",
  t(coef(m6))
),
data.frame(
  model = "Deducted 0.5s time",
  t(coef(m7))
)
)

kable(model_df, digits = 2, booktabs = TRUE)

```

	model	MSS	TAU	MAC	PMAX	time_correction	distance_correction
172	True time	9.00	1.30	6.92	15.6	0	0
	Added 0.5s time	9.91	2.34	4.23	10.5	0	0
	Deducted 0.5s time	10.08	1.86	5.43	13.7	0	0

173 As can be seen from the example, all estimated parameters are affected by an error in synchronization  
 174 of time with velocity (with MSS being the least affected in this example). The potential solution  
 175 incorporated into the **shorts** package involves estimation of the *time correction* parameter using the  
 176 following equation:

$$v(t) = MSS \times (1 - e^{-\frac{t + \text{time correction}}{TAU}}) \quad (6)$$

177 This model is incorporated in the `model_using_radar_with_time_correction()` function:

```

# With time added
m8 <- model_using_radar_with_time_correction(
  velocity = df$velocity,
  time = df$`0.5s added`
)
coef(m8)
#>           MSS           TAU           MAC
#>           9.00           1.30           6.92
#>           PMAX   time_correction distance_correction
#>          15.58           -0.50           0.00

# With time deducted
m9 <- model_using_radar_with_time_correction(
  velocity = df$velocity,
  time = df$`0.5s deducted`
)
coef(m9)
#>           MSS           TAU           MAC
#>           9.00           1.30           6.92
#>           PMAX   time_correction distance_correction
#>          15.58           0.50           0.00

```

178 When using `predict_XXX()` family of functions, one can provide estimated time correction to get  
 179 predictions at original time scale.

```

# Using the true time
predict_velocity_at_time(
  time = df$`true time`,
  MSS = m5$parameters$MSS,

```

```

    TAU = m5$parameters$TAU
  )
#> [1] 0.00 4.83 7.07 8.11 8.59 8.81 8.91

# Using time with sync issues
predict_velocity_at_time(
  time = df$`0.5s added`,
  MSS = m8$parameters$MSS,
  TAU = m8$parameters$TAU,
  time_correction = m8$parameters$time_correction
)
#> [1] 0.0000782 4.8299729 7.0681475 8.1053182 8.5859434 8.8086652
#> [7] 8.9118746

```

#### 180 4.1.1 Mixed-model approach

181 When it comes to mixed-model approach, time correction can be modeled as a fixed effect or random  
 182 effect using the `mixed_model_using_radar_with_time_correction()` function.

```

# Adding 0.5s to radar_gun_data
radar_gun_data$time <- radar_gun_data$time + 0.5

# Mixed model with time correction being fixed effect
m10 <- mixed_model_using_radar_with_time_correction(
  radar_gun_data,
  time = "time",
  velocity = "velocity",
  athlete = "athlete",
  random = MSS + TAU ~ 1
)

# Mixed model with time correction being random effect
m11 <- mixed_model_using_radar_with_time_correction(
  radar_gun_data,
  time = "time",
  velocity = "velocity",
  athlete = "athlete",
  random = MSS + TAU + time_correction ~ 1
)

```

## 183 4.2 Problems at the start when using split times

184 Let's imagine we have two twin brothers with same short sprint characteristics: MSS equal to  $9\text{ ms}^{-1}$ ,  
 185 TAU equal to 1.3, and MAC equal to  $6.92\text{ ms}^{-2}$ . Let's call them John and Jack. They both perform 40m  
 186 sprint using timing gates set at 5, 10, 20, 30, and 40 m. The initial timing gate at the start (i.e.,  $d = 0\text{ m}$ )  
 187 serves to activate the timing system (i.e., when they cross the beam).

188 John represents the *theoretical model*, in which we assume that the initial force production and the  
 189 timing initiation are perfectly synchronized. Jack, on the other hand, represents a *practical model*, and  
 190 decides to move slightly behind the initial timing gate (i.e. for 0.5 m) and use body rocking to initiate  
 191 the sprint start. In other words, Jack is using a *flying start*, a common scenario when testing field sports  
 192 athletes.

```

MSS <- 9
TAU <- 1.3
MAC <- MSS / TAU

split_times <- tibble(

```

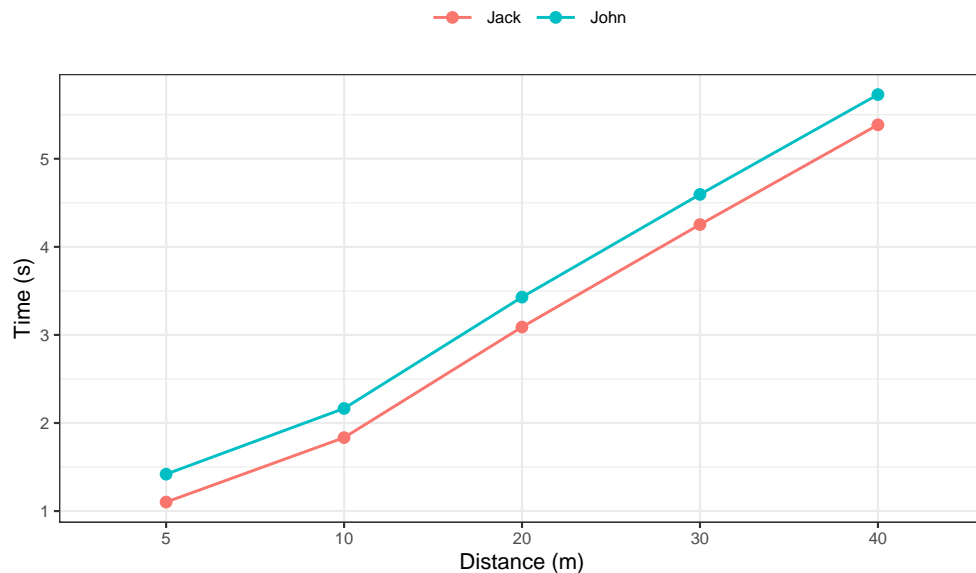
```

distance = c(5, 10, 20, 30, 40),
john.time = predict_time_at_distance(distance, MSS, TAU),

# Jack's performance
jack.distance = distance + 0.5,
jack.true.time = predict_time_at_distance(jack.distance, MSS, TAU),
time_05m = predict_time_at_distance(0.5, MSS, TAU),
jack.time = jack.true.time - time_05m
)

```

193 Here is a graphical representation of the sprint splits (please refer to the Supplemental files for the R  
194 code):



195

196 Using the following code, we can see the differences in estimated MSS and TAU parameters:

```

# Since this is a perfect simulation and stats::nls will complain
# we need to add very small noise, or measurement error to the times
set.seed(1667)
rand.noise <- rnorm(nrow(split.times), 0, 10^-5)
split.times$john.time <- split.times$john.time + rand.noise
split.times$jack.time <- split.times$jack.time + rand.noise

john.profile <- modelusing_splits(
  distance = split.times$distance,
  time = split.times$john.time
)

jack.profile <- modelusing_splits(
  distance = split.times$distance,
  time = split.times$jack.time
)

sprint.parameters <- rbind(
  coef(john.profile),
  coef(jack.profile)
)

```



```
)

rownames(sprint_parameters) <- c("John", "Jack")

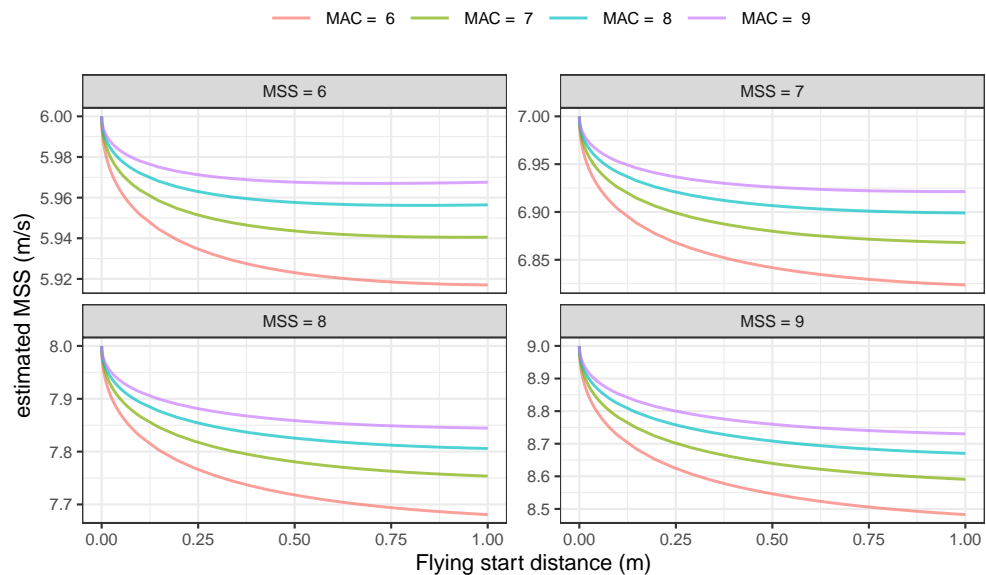
kable(sprint_parameters, digits = 2, booktabs = TRUE)
```

		MSS	TAU	MAC	PMAX	time_correction	distance_correction
197	John	9.00	1.3	6.92	15.6	0	0
	Jack	8.49	0.7	12.06	25.6	0	0

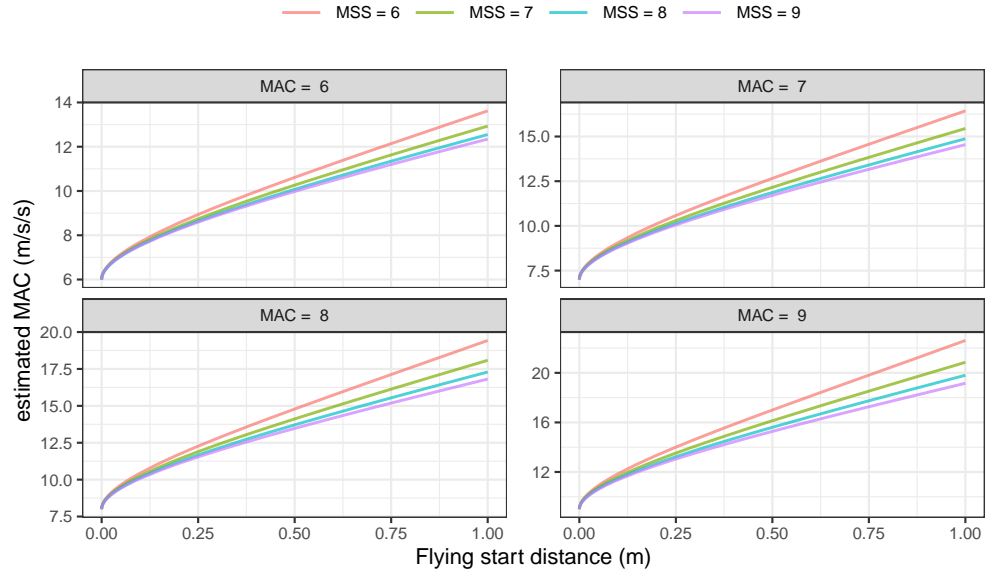
198 As can be seen from the results, a flying start yields biased estimates, particularly for the TAU, MAC  
199 and PMAX.

200 To explore this further, we have run a simple simulation with 5, 10, 20, 30, 40, and 50 m splits, with  
201 MSS and MAC varying from 6 to 9 ( $ms^{-1}$  and  $ms^{-2}$  respectively), and flying start distance varying from  
202 0 to 1 m (please refer to the Supplemental files for the R code). With a simulation dataset, we can check  
203 the model estimates and predictions, given the flying start distance.

204 The following figure demonstrates the effect of flying start distance on estimated MSS:



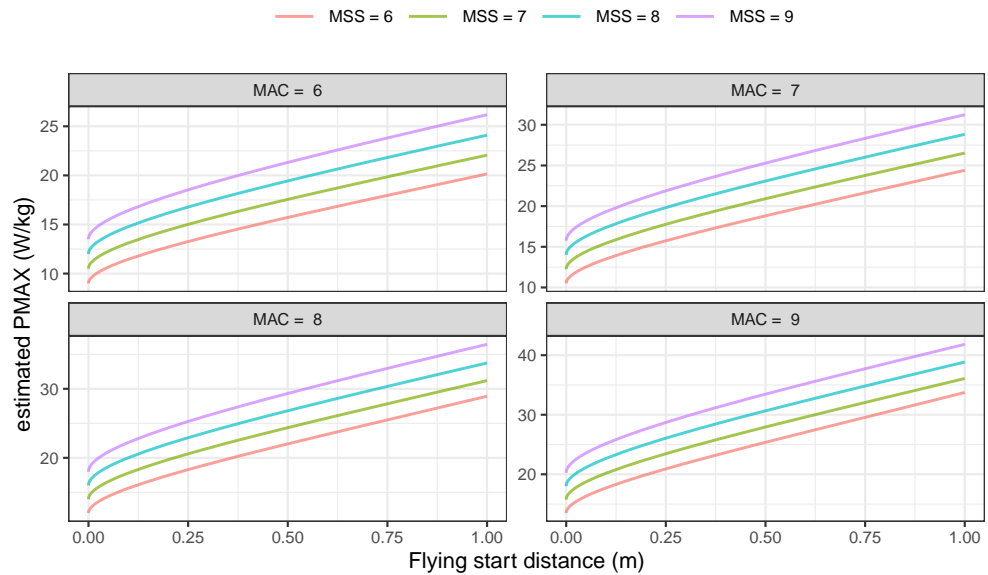
206 As can be seen from the figure, MSS is underestimated as flying start distance increases. The following  
207 image demonstrates the effect of flying start distance on estimated MAC:



208

209 MAC (and also TAU) are highly affected by the flying start distance, and from the figure we can notice  
 210 that MAC is overestimated as flying start distance increases.

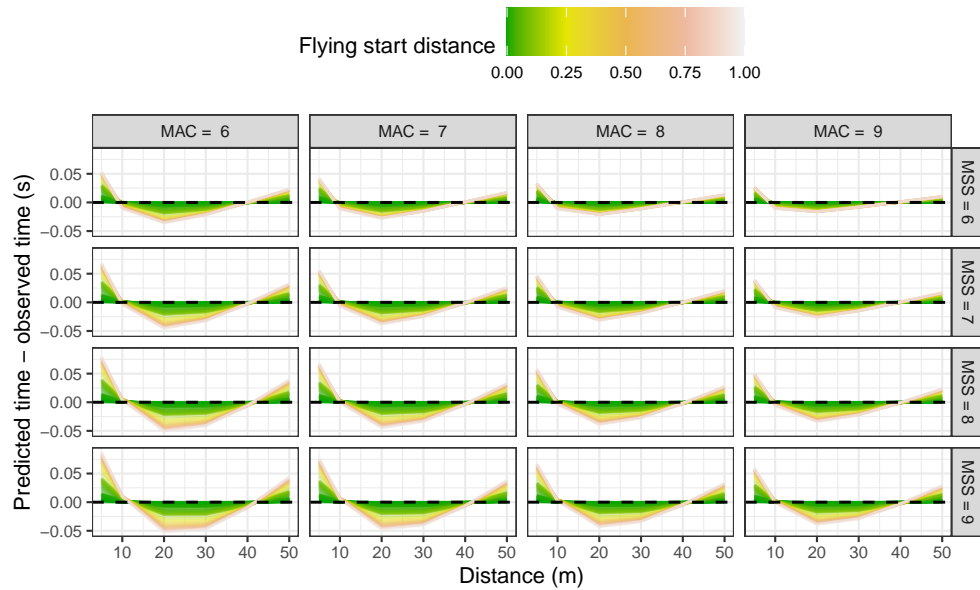
211 And finally, the following image demonstrates the effect of flying start distance on estimated PMAX:



212

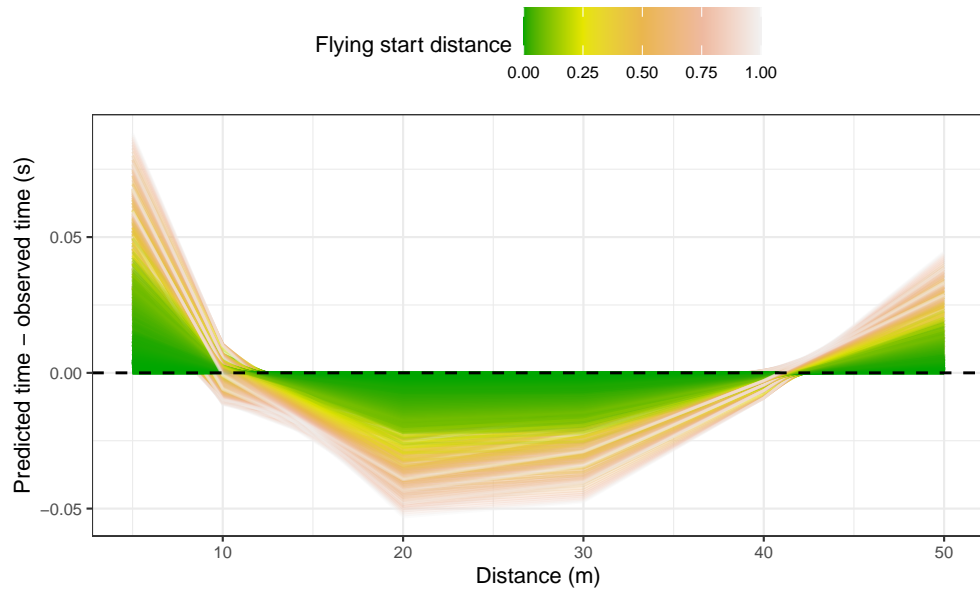
213 Estimated PMAX is also overestimated as flying start distance increases.

214 Model residuals are also affected by flying start distance. The shape of residuals distribution depends  
 215 on number and splits utilized (e.g., 10, 20, 30, 40 m versus 5, 15, 30 m), but here we can see the effect of  
 216 the flying start distance on the model residuals per split distance utilized in our simulation:



217

218 If we merge individual facets (i.e., combinations of MSS and MAC), we can get simpler figure  
 219 conveying issues with residuals when there is a flying start:



220

221 Clearly, any type of flying start where there is a difference between initial force production and start  
 222 time can result in biased parameters and predictions. Since maximal sprint speed is difficult to improve,  
 223 the effects of start inconsistencies can mask effects of the training intervention. It is thus crucial to  
 224 standardize the start when testing and implementing the following techniques when using the **shorts**  
 225 package.

#### 226 4.2.1 How to overcome missing the initial force production when using timing gates?

227 A potential solution is to use a correction factor - the recommendation in the literature is +0.5 s (Thomas  
 228 A. Haugen, Breitschädel, and Seiler 2020, 2019). Interestingly, the average difference between using  
 229 timing gates and a block start for 40 m sprint time was 0.27 s (Thomas A. Haugen, Tønnessen, and Seiler  
 230 2012). So, while a timing correction factor is warranted to avoid subsequent errors in estimates of kinetic  
 231 variables (e.g., overestimate power), a correction factor that is too large will have the opposite effect (e.g.,  
 232 underestimate power).

233 Rather than providing *apriori* time correction from the literature, **shorts** package provides an estima-  
 234 tion of this parameter from the data provided, together with MSS and TAU. Exactly the same method is  
 235 suggested by Stenroth, Vartiainen, and Karjalainen (2020), named *time shift method*, and the estimated  
 236 parameter named *time shift parameter*. We have named this parameter *time correction* to be in agreement  
 237 with the parameter introduced in Problems with time sync with radar gun section of this paper, as well as  
 238 the available literature.

239 When implementing time correction, equation (5) becomes:

$$t(d) = TAU \times W(-e^{\frac{-d}{MSS \times TAU}} - 1) + \frac{d}{MSS} + TAU - \text{time correction} \quad (7)$$

240 To estimate time correction parameter, we use `model_using_splits_with_time_correc-`  
 241 `tion()` function. Here is how we can estimate Jack parameters using either provided time correction  
 242 (e.g., +0.3 and +0.5 s) or estimated time correction:

```
jack_profile_fixed_time_short <- model_using_splits(
  distance = split_times$distance,
  time = split_times$jack_time,
  time_correction = 0.3
)

jack_profile_fixed_time_long <- model_using_splits(
  distance = split_times$distance,
  time = split_times$jack_time,
  time_correction = 0.5
)

jack_profile_time_estimated <- model_using_splits_with_time_correction(
  distance = split_times$distance,
  time = split_times$jack_time
)

jack_parameters <- rbind(
  coef(john_profile),
  coef(jack_profile),
  coef(jack_profile_fixed_time_short),
  coef(jack_profile_fixed_time_long),
  coef(jack_profile_time_estimated)
)

rownames(jack_parameters) <- c(
  "John",
  "Jack - No corrections",
  "Jack - Fixed time correction (+0.3s)",
  "Jack - Fixed time correction (+0.5s)",
  "Jack - Estimated time correction"
)

kable(jack_parameters, digits = 2, booktabs = TRUE) %>%
  kable_styling(latex_options = c("scale_down", "hold_position"))
```

243 In Jack's case, both +0.3 s fixed time correction and time correction estimation yield parameters closer  
 244 to John's (i.e. true parameters).

245 Another model definition, which is a novel approach implemented in the **shorts** package, is to utilize  
 246 *distance correction*, besides time correction. Thus, equation (5) becomes:

	MSS	TAU	MAC	PMAX	time_correction	distance_correction
John	9.00	1.30	6.92	15.6	0.00	0
Jack - No corrections	8.49	0.70	12.06	25.6	0.00	0
Jack - Fixed time correction (+0.3s)	9.00	1.25	7.19	16.2	0.30	0
Jack - Fixed time correction (+0.5s)	9.62	1.77	5.43	13.1	0.50	0
Jack - Estimated time correction	8.96	1.22	7.37	16.5	0.28	0

$$t(d) = TAU \times W(-e^{\frac{-d + \text{distance correction}}{MSS \times TAU}} - 1) + \frac{d + \text{distance correction}}{MSS} + TAU - \text{time correction} \quad (8)$$

247 This model is implemented in `model_using_splits_with_corrections()` function. Below  
248 are the model estimates:

```
jack_profile_distance_correction <- model_using_splits_with_corrections(
  distance = split_times$distance,
  time = split_times$jack_time
)

jack_parameters <- rbind(
  coef(john_profile),
  coef(jack_profile),
  coef(jack_profile_fixed_time_short),
  coef(jack_profile_fixed_time_long),
  coef(jack_profile_time_estimated),
  coef(jack_profile_distance_correction)
)

rownames(jack_parameters) <- c(
  "John",
  "Jack - No corrections",
  "Jack - Fixed time correction (+0.3s)",
  "Jack - Fixed time correction (+0.5s)",
  "Jack - Estimated time correction",
  "Jack - Estimated distance correction"
)

kable(jack_parameters, digits = 2, booktabs = TRUE) %>%
  kable_styling(latex_options = c("scale_down", "hold_position"))
```

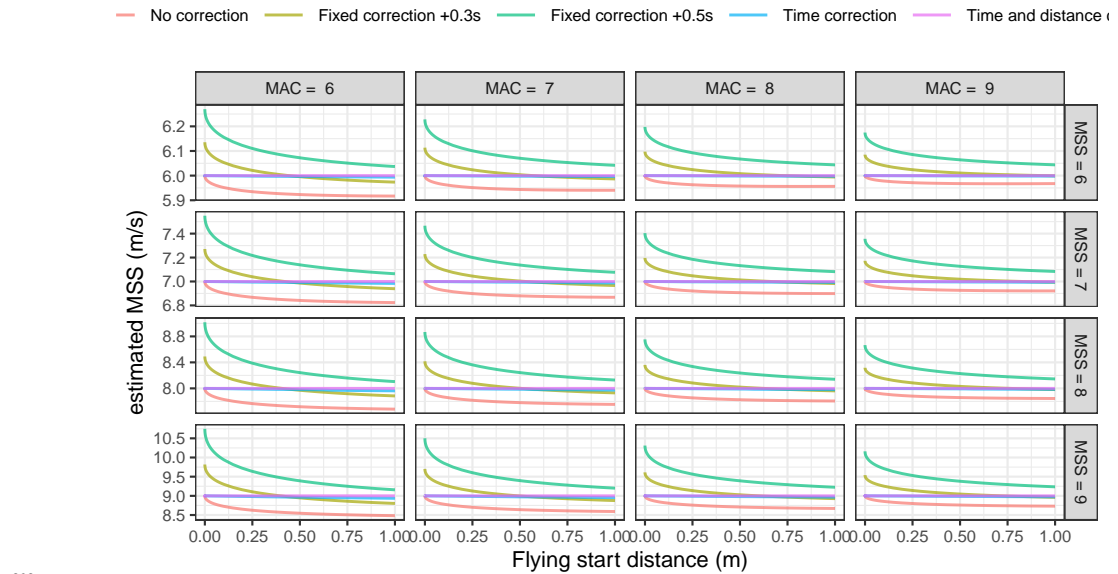
	MSS	TAU	MAC	PMAX	time_correction	distance_correction
John	9.00	1.30	6.92	15.6	0.00	0.0
Jack - No corrections	8.49	0.70	12.06	25.6	0.00	0.0
Jack - Fixed time correction (+0.3s)	9.00	1.25	7.19	16.2	0.30	0.0
Jack - Fixed time correction (+0.5s)	9.62	1.77	5.43	13.1	0.50	0.0
Jack - Estimated time correction	8.96	1.22	7.37	16.5	0.28	0.0
Jack - Estimated distance correction	9.00	1.30	6.92	15.6	0.40	0.5

249 As can be seen from the results, adding distance correction results in correctly estimating Jack's sprint  
250 parameters. There are a few issues with this model definition. Besides being novel and still not validated  
251 with actual data, distance correction model has four parameters to estimate, which implies that at least five  
252 sprint splits are needed. This imposes practical limitations, since acquiring six timing gate (one for the start  
253 and five for splits) might be practically troublesome. One strategy that is sometimes implemented is adding

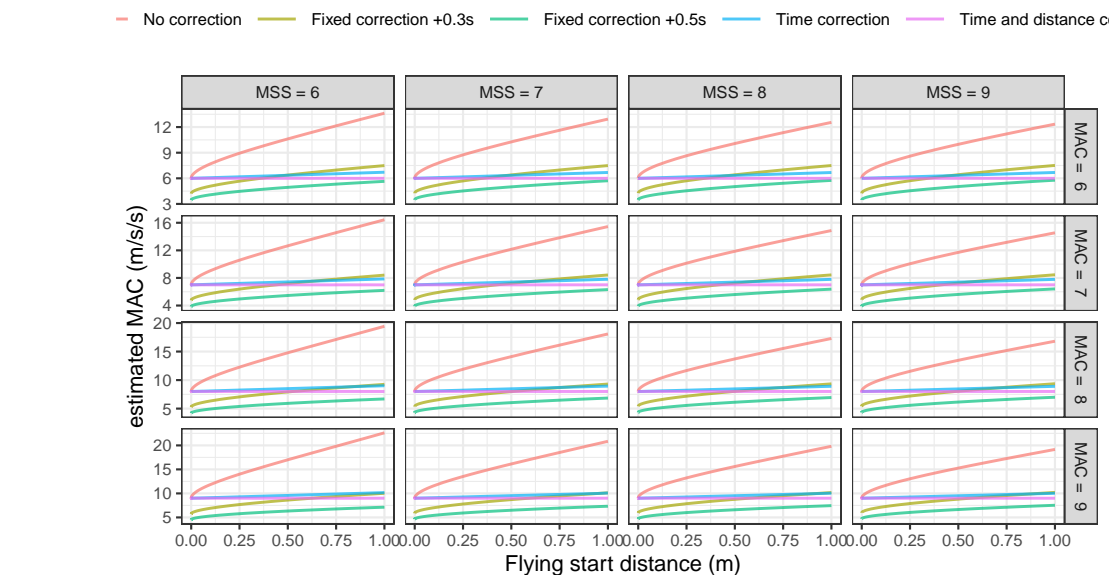
zeros to the sample (i.e.,  $t = 0$  and  $d = 0$ ), which increase the number of observations. Unfortunately, this strategy should not be implemented, as explained later in the Should we add zero to the sample? section of this paper.

We will get back to these issues later, but we can examine how these models (no correction, fixed time correction, estimated time correction, and estimated time and distance correction) perform using simulated data with varying flying start distance (please refer to the Supplemental files for the R code).

As can be seen from the next figure, the estimated time correction model estimates MSS almost perfectly, while the estimated time and distance correction model estimates MSS perfectly.

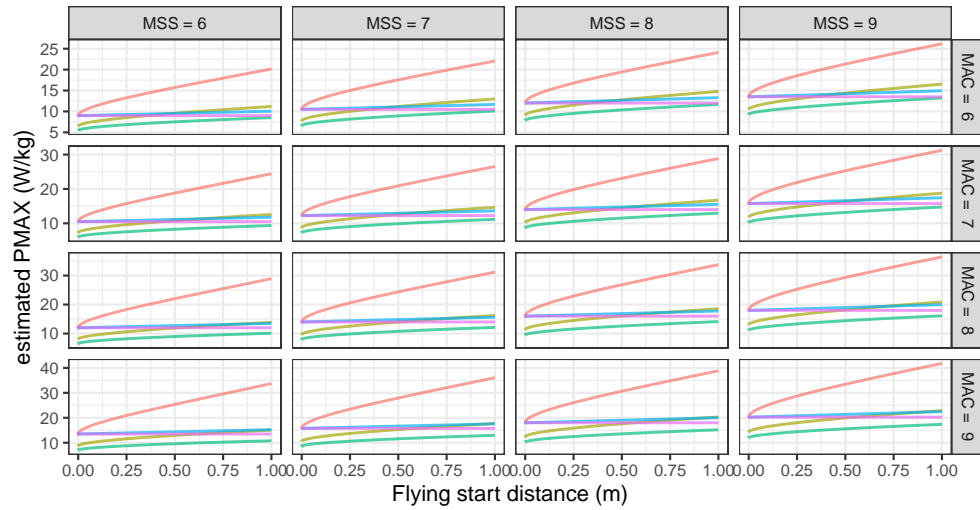


Similar outcomes are observed for the MAC parameter. The time and distance corrections model performs perfectly, while the time correction model performs almost as good.



PMAX demonstrates the same properties as MSS and MAC.

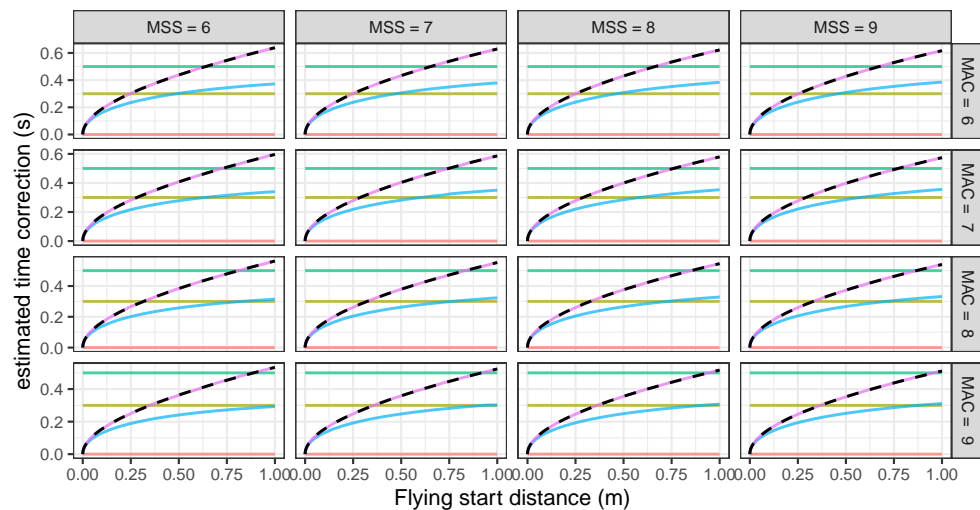
— No correction — Fixed correction +0.3s — Fixed correction +0.5s — Time correction — Time and distance c



267

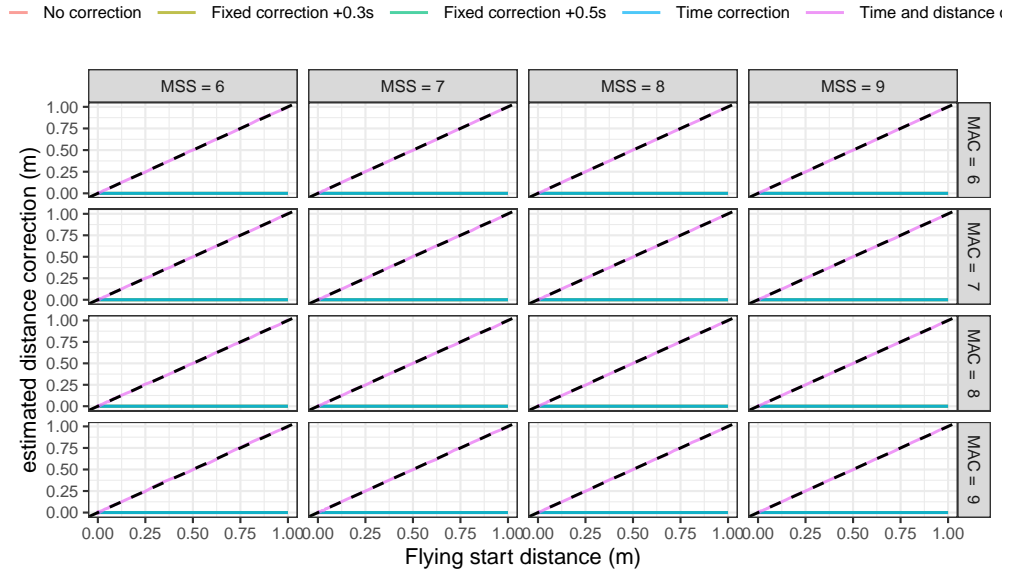
268 The following figure depicts estimated time correction, and as can be seen, only the time and distance  
 269 correction model estimated the time correction correctly (i.e., the *stolen time*; indicated by the dashed line  
 270 on the figure).

— No correction — Fixed correction +0.3s — Fixed correction +0.5s — Time correction — Time and distance c



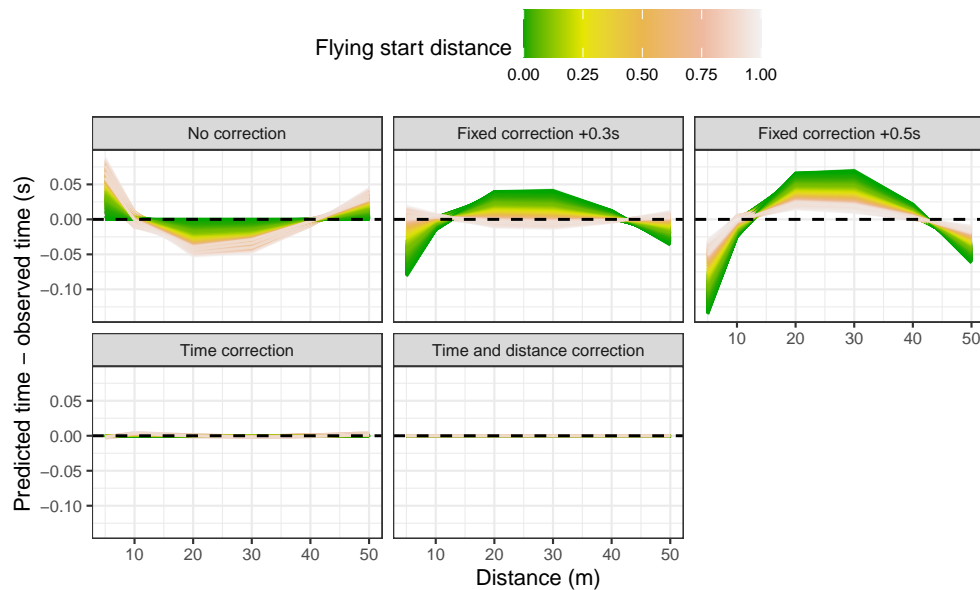
271

272 The next figure depicts estimated distance correction, and same as with the time correction, only the  
 273 time and distance correction model estimated the distance correction correctly (i.e., flying start distance;  
 274 indicated by the dashed line on the figure, which represents *identity line* since flying start distance is  
 275 already on the x-axis).



276

277 The following figure depicts model residuals against the distance, and as can be seen, time correction  
 278 and time and distance correction models performs much better than no correction and fixed correction  
 279 models:



280

281 The outcomes from the simulation data clearly demonstrates that the time correction and time and  
 282 distance correction models represent sound improvements in parameter estimation and model fit compared  
 283 to no corrections model and fixed correction model when attempting to overcome the flying start issues.  
 284 Since the time correction model is simpler and requires three parameters to be estimated, it might be  
 285 practically more useful than the time and distance correction model, which requires four parameters  
 286 estimation and thus more than five timing gates and sprint splits.

287 Time correction and time and distance corrections are also implemented in the mixed-models  
 288 using `mixed_model_using_splits_with_time_correction()` and `mixed_model_using_splits_with_corrections()`. We will showcase their use at the end of this paper.

#### 290 4.2.2 Simulation of additional starting issues

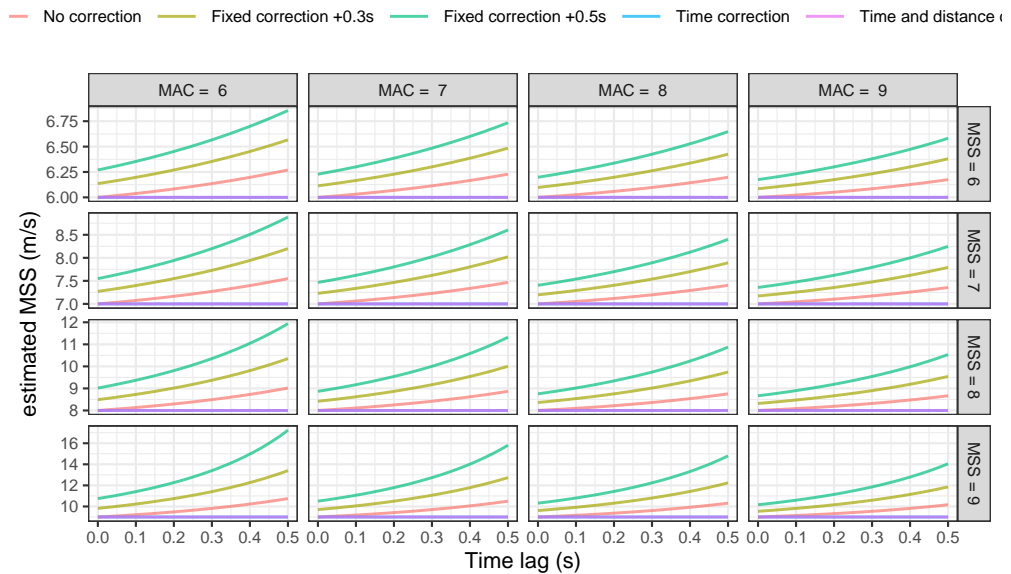
291 Starting behind the initial timing gate represent only one issue (i.e., flying start). In this section, we simu-  
 292 late one more issue to check the sensitivity of the presented models to other (less common) perturbations



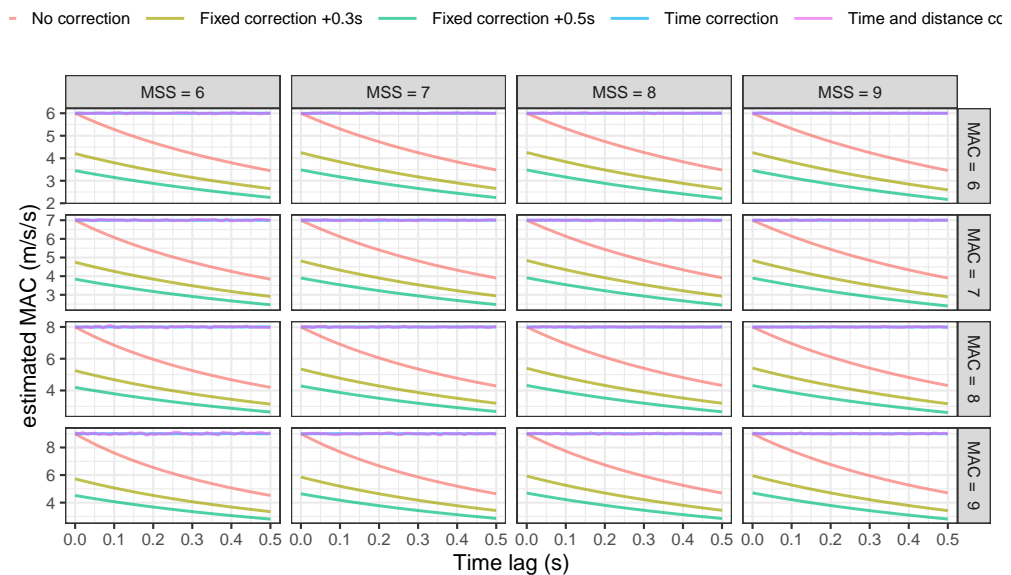
when performing field testing.

One issue that might happen with timing gates is triggering the timing system before the sprint is initiated (e.g., by cutting the beam with an arm swing prematurely). This is very similar to the situation when timing starts on a signal (i.e., gun during 100 m sprint race) and there is *reaction time* (RT) involved. Both of these scenarios represent *time lag* that is added to the split times. We have simulated the effect of this time lag on model estimates and predictions (please refer to the Supplemental files for the R code).

From the figure below it can be seen that time lag affects estimated MSS for the the model without correction and fixed correction model. Time correction and time and distance corrections models correctly estimated MSS.

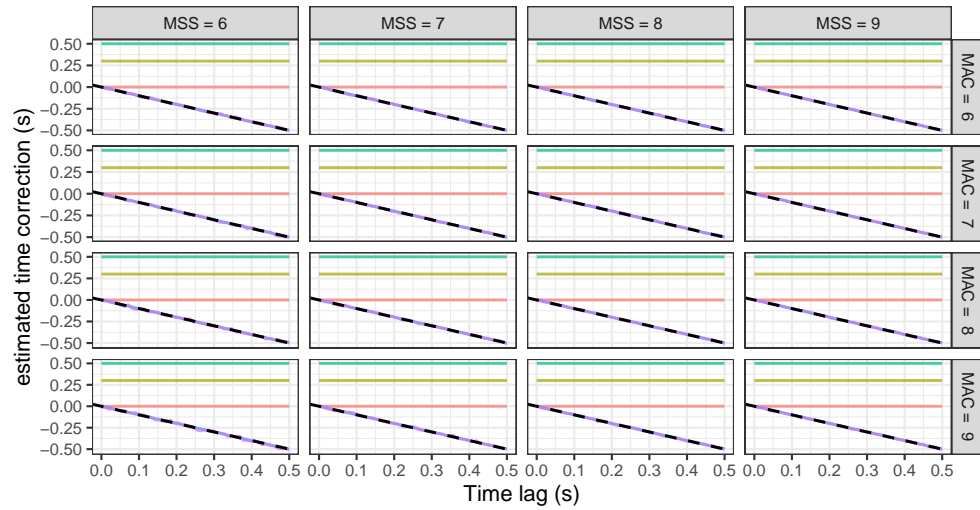


From the next figure it can be seen that time lag affects estimated MAC for the the model without correction and fixed correction models. Time correction and time and distance corrections model correctly estimated MAC.



The figure below depicts correctly identified time lag (i.e. using time correction parameter) using time correction and time and distance corrections models.

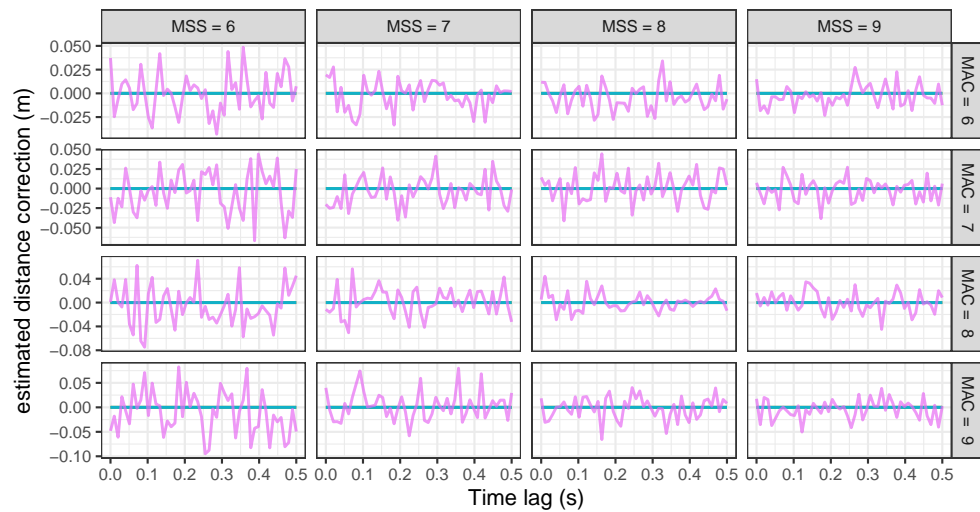
— No correction — Fixed correction +0.3s — Fixed correction +0.5s — Time correction — Time and distance



309

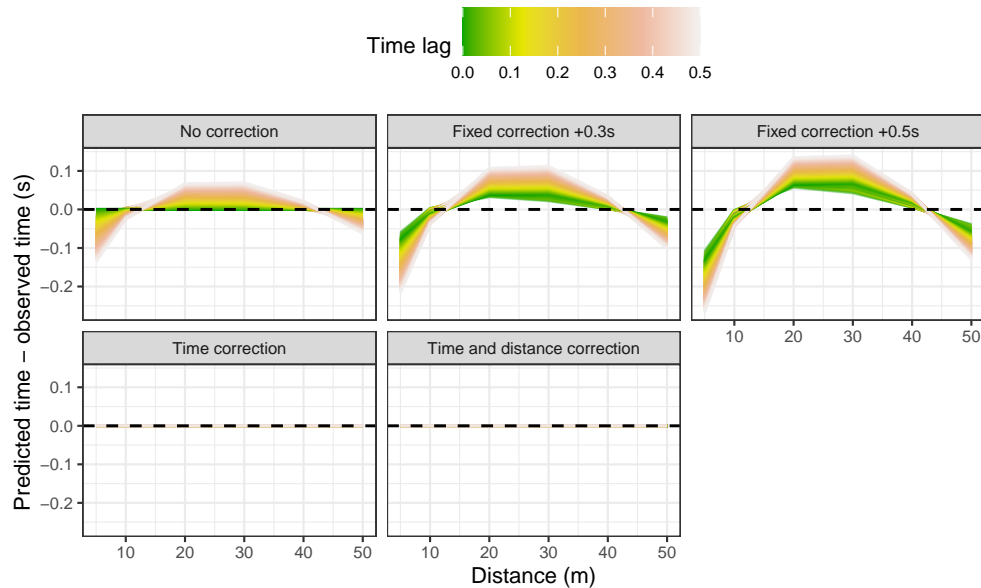
310 The next figure depicts estimated distance correction for the time and distance correction model. The  
 311 estimated distance correction parameters looks jumpy due to random noise that we have to added to allow  
 312 model fit, as well as the model estimation error.

— No correction — Fixed correction +0.3s — Fixed correction +0.5s — Time correction — Time and distance



313

314 The following figure depicts residuals (i.e., predicted time minus observed time).



315

316 There are few other starting issues worth mentioning. For example, if the initial timing gate has a  
 317 time delay (i.e., once triggered, there is a time delay before the timing starts). In this case, time lag is a  
 318 negative number since it reduces the split times. Another common issue with timing gates in the practical  
 319 field settings is the bad measurement of the distance and thus bad positions of the timing gates.

320 The number and distances of the timing gates can also affect the precision of the estimated sprint  
 321 parameters (Thomas A. Haugen, Breitschädel, and Samozino 2020; Thomas A. Haugen, Tønnessen, and  
 322 Seiler 2012).

323 In field testing, multiple starting issues can be present. For example, one might have a bad position of  
 324 the initial gate, athlete might be moved back but also manage to trigger the gate before the start commence.  
 325 More elaborate simulation is beyond the scope of the current paper.

### 326 4.3 Should we add zero to the sample?

327 Fellow sports scientists are often considering adding  $t = 0$  s at  $d = 0$  m to the collected split times with  
 328 the aim of increasing the number of observations. The question is whether this strategy is sound and if it  
 329 should be employed. The short answer is no, it shouldn't, particularly if there are flying start issues. In  
 330 the following example, we are demonstrating the issue when zeros are added to the sample when fitting  
 331 multiple models with the known true parameters:

```
# Create split times from known MSS and TAU
df <- tibble(
  distance = c(5, 10, 20, 30, 40),
  time = predict_time_at_distance(
    distance,
    MSS = 9,
    TAU = 1.3
  )
) %>%
  mutate(
    # Add random noise to time
    time = time + rnorm(n(), 0, 10^-5),
    gate_time = time - 0.1
  )

# Model without time correction
m.no.correction <- model_using_splits(
```

```

    distance = df$distance,
    time = df$gate_time
  )

  # Model without time correction, but with zeros added
  m_no_correction_zero <- model.using_splits(
    distance = c(0, df$distance),
    time = c(0, df$gate_time)
  )

  # Model without adding zeros for the start
  m_no_zero <- model.using_splits_with_time_correction(
    distance = df$distance,
    time = df$gate_time
  )

  # Model with added zeros for the start (d=0 and t=0)
  m_with_zero <- model.using_splits_with_time_correction(
    distance = c(0, df$distance),
    time = c(0, df$gate_time)
  )

  # Print results
  res_df <- data.frame(
    model = c(
      "Without time correction",
      "Without time correction with zeros added",
      "With time correction",
      "With time correction with zeros added"
    ),
    rbind(
      coef(m_no_correction),
      coef(m_no_correction_zero),
      coef(m_no_zero),
      coef(m_with_zero)
    )
  )

  kable(res_df, digits = 2, booktabs = TRUE) %>%
    kable_styling(latex_options = c("scale_down", "hold_position"))

```

model	MSS	TAU	MAC	PMAX	time_correction	distance_correction
Without time correction	8.78	1.09	8.06	17.7	0.00	0
Without time correction with zeros added	8.78	1.09	8.06	17.7	0.00	0
With time correction	9.00	1.30	6.92	15.6	0.10	0
With time correction with zeros added	8.79	1.10	7.97	17.5	0.01	0

332 As can be seen from the output, only the model with time correction is able to correctly recover true  
 333 sprint parameters, but adding zeros to the sample in this case, results in MSS and TAU estimates very  
 334 close to the estimates of the model without time corrections. Thus, adding zeros to the sample nullifies  
 335 the potential benefits of using time correction model and should be avoided in practice.

## 336 5 LEAVE-ONE-OUT CROSS-VALIDATION

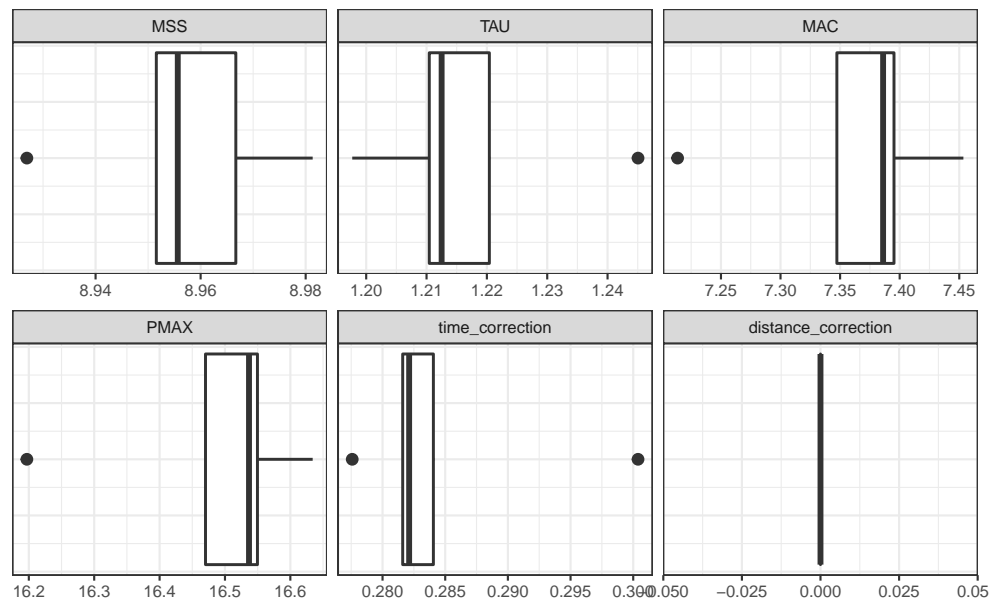
337 To estimate parameter stability, model over-fitting, and performance on the unseen data, **shorts** model  
 338 function comes with implemented *leave-one-out cross validation* (LOOCV) (James et al. 2017; Jovanović  
 339 2020; Kuhn and Johnson 2018). LOOCV involves a simple, yet powerful procedure, of removing each  
 340 observation, rebuilding the model, and making predictions for that removed observation. This process is  
 341 repeated for each observation in the model dataset. LOOCV allows one to check estimated parameters  
 342 stability, and model performance on the unseen data.

343 Let's perform LOOCV using Jack's data and the time correction model:

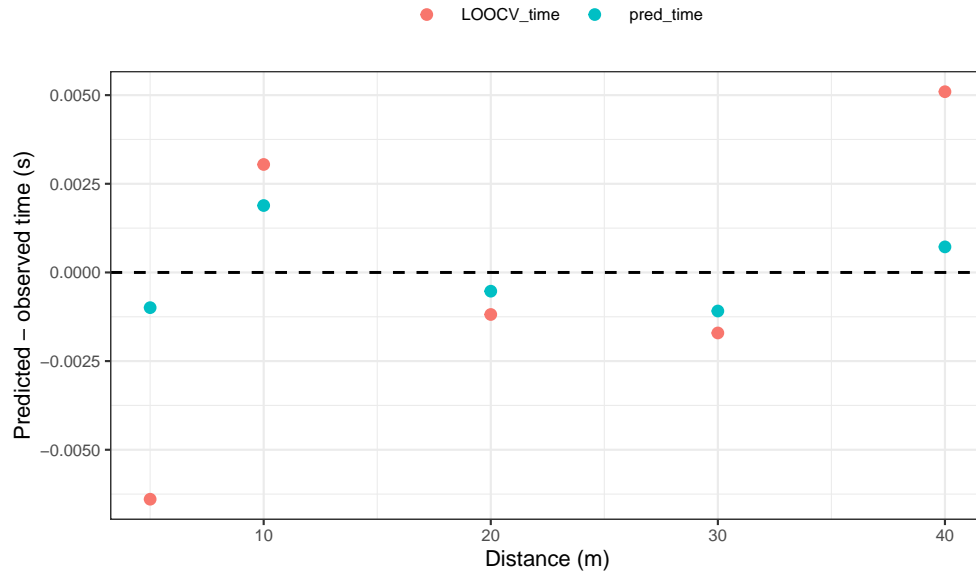
```
jack_LOOCV <- model_using_splits_with_time_correction(  
  distance = split_times$distance,  
  time = split_times$jack_time,  
  LOOCV = TRUE  
)
```

344 The model print output provides training dataset estimates and model performance, as well as LOOCV  
 345 estimates and model performance.

346 Next we plot estimated parameters across LOOCV folds (please refer to the Supplemental files for the  
 347 R code):



349 Here is the plot of the training and LOOCV residuals:



350

351 As expected, the model has more issues predicting unseen split times for both short or long distances.  
 352 Please note, that since LOOCV removes one observation, if the model estimates three parameters, then at  
 353 least five observations are needed, since we need to make sure the model can be estimated once a single  
 354 observation is removed. LOOCV can also be implemented with the mixed-effects models in the **shorts**  
 355 package.

## 356 6 EXAMPLE ANALYSIS

357 Let's utilize demonstrated functionalities of the **shorts** package using real-world data. The first dataset  
 358 comes from Usain Bolt's performance from IAAF World Championship held in London, 2017, and the  
 359 second dataset involve Jason Vescovi's sample data for 52 female soccer and field hockey athletes which  
 360 comes with the **shorts** package (see `?vescovi`).

### 361 6.1 Usain Bolt's run from London 2017

362 The following dataset represents Usain Bolt's race in the finals at the IAAF World Championship held  
 363 in London, 2017. Since reaction time enters the splits, we want to see how that will affect the model  
 364 estimates, and particularly, if the estimated time correction model will pick-up reaction time.

365 For the sake of this analysis, only 10 m splits over 60 m race distance are used.

```

bolt_reaction_time <- 0.183

bolt_distance <- c(10, 20, 30, 40, 50, 60)
bolt_time <- c(1.963, 2.983, 3.883, 4.763, 5.643, 6.493)

# No corrections model
bolt_m1 <- model_using_splits(
  distance = bolt_distance,
  time = bolt_time
)

# Model with reaction time as fixed time correction
bolt_m2 <- model_using_splits(
  distance = bolt_distance,
  time = bolt_time,
  time_correction = -bolt_reaction_time
)

```

```

# Model with estimated time correction
bolt_m3 <- model_using_splits_with_time_correction(
  distance = bolt_distance,
  time = bolt_time
)

# Model with estimated time correction, but deducted reaction time
bolt_m4 <- model_using_splits_with_time_correction(
  distance = bolt_distance,
  time = bolt_time - bolt_reaction_time
)

# Model with estimated time and distance corrections
bolt_m5 <- model_using_splits_with_corrections(
  distance = bolt_distance,
  time = bolt_time
)

# Model with estimated time and distance corrections and
# deducted reaction time
bolt_m6 <- model_using_splits_with_corrections(
  distance = bolt_distance,
  time = bolt_time - bolt_reaction_time
)

bolt_model <- rbind(
  data.frame(
    model = "No correction",
    t(coef(bolt_m1))
  ),
  data.frame(
    model = "No correction - RT",
    t(coef(bolt_m2))
  ),
  data.frame(
    model = "Time correction",
    t(coef(bolt_m3))
  ),
  data.frame(
    model = "Time correction - RT",
    t(coef(bolt_m4))
  ),
  data.frame(
    model = "Distance correction",
    t(coef(bolt_m5))
  ),
  data.frame(
    model = "Distance correction - RT",
    t(coef(bolt_m6))
  )
)

kable(bolt_model, digits = 2, booktabs = TRUE) %>%
  kable_styling(latex_options = c("scale_down", "hold_position"))

```

model	MSS	TAU	MAC	PMAX	time_correction	distance_correction
No correction	12.1	1.56	7.77	23.6	0.00	0.00
No correction - RT	11.7	1.21	9.74	28.6	-0.18	0.00
Time correction	11.7	1.20	9.76	28.6	-0.18	0.00
Time correction - RT	11.7	1.20	9.76	28.6	0.00	0.00
Distance correction	11.6	0.85	13.56	39.3	-0.81	-3.98
Distance correction - RT	11.6	0.85	13.56	39.3	-0.63	-3.98

366 Here is the model estimate of the time and distance it takes for Bolt to reach 99% of MSS. Please note  
367 that we are not using distance and time correction parameters, since we want these estimates to be on the  
368 time/distance scale aligned with the actual sprint start, not the measurement scale.

```

bolt_model <- bolt_model %>%
  group_by(model) %>%
  mutate(
    dist_99_MSS = find_velocity_critical_distance(
      MSS = MSS, TAU = TAU,
      # time_correction = time_correction,
      # distance_correction = distance_correction,
      percent = 0.99
    ),
    time_99_MSS = find_velocity_critical_time(
      MSS = MSS, TAU = TAU,
      # time_correction = time_correction,
      percent = 0.99
    )
  )

kable(bolt_model[c(1, 8, 9)], digits = 2, booktabs = TRUE)

```

model	dist_99_MSS	time_99_MSS
No correction	68.7	7.20
No correction - RT	51.1	5.55
Time correction	51.0	5.54
Time correction - RT	51.0	5.54
Distance correction	35.8	3.94
Distance correction - RT	35.8	3.94

## 370 6.2 Vescovi data

371 The data from Vescovi represents a sub-set of data from a total of 220 high-level female athletes (151  
372 soccer players and 69 field hockey players). Using a random number generator, a total of 52 players (35  
373 soccer and 17 field hockey) were selected for the sample dataset.

374 The protocol for assessing linear sprint speed has been described previously (Vescovi 2014, 2016,  
375 2012) and was identical for each cohort. Briefly, all athletes performed a standardized warm-up that  
376 included general exercises such as jogging, shuffling, multi-directional movements, and dynamic stretching  
377 exercises. Infrared timing gates (Brower Timing, Utah) were positioned at the start line and at 5, 10,  
378 20, 30, and 35 m at a height of approximately 1.0 m. Participants stood with their lead foot positioned  
379 approximately 5 cm behind the initial infrared beam (i.e., start line). Only forward movement was  
380 permitted (no leaning or rocking backwards) and timing started when the laser of the starting gate was  
381 triggered. The best 35 m time, and all associated split times were kept for analysis.

382 Below is the mixed-effects models analysis of the dataset.



```

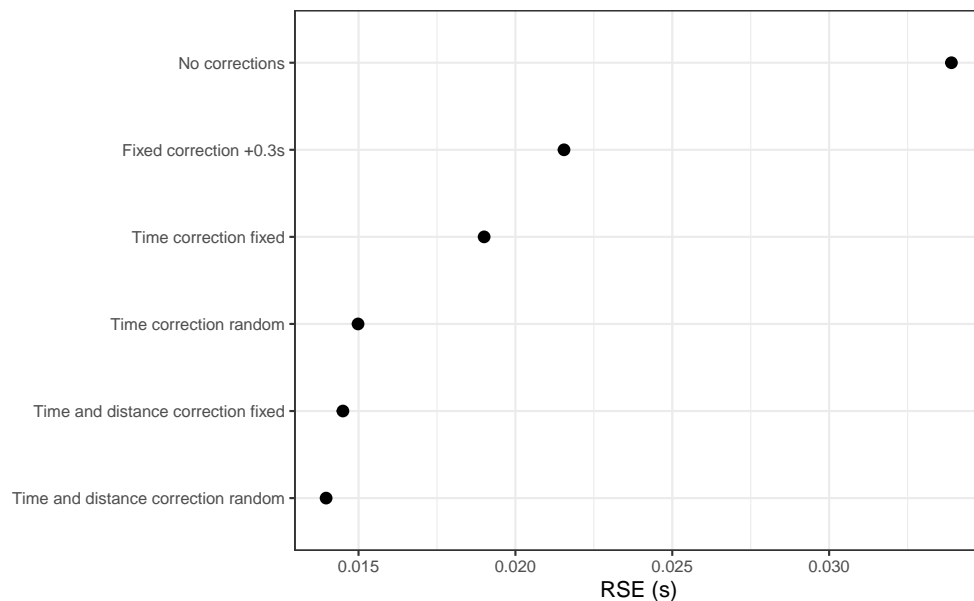
data("vescovi")

# Convert data to long
df <- vescovi %>%
  select(1:13) %>%
  # slice(1:10) %>%
  pivot_longer(
    cols = 9:13,
    names_to = "distance",
    values_to = "time"
  ) %>%
  mutate(
    distance = as.numeric(str_extract(distance, "[0-9]+"))
  )

```

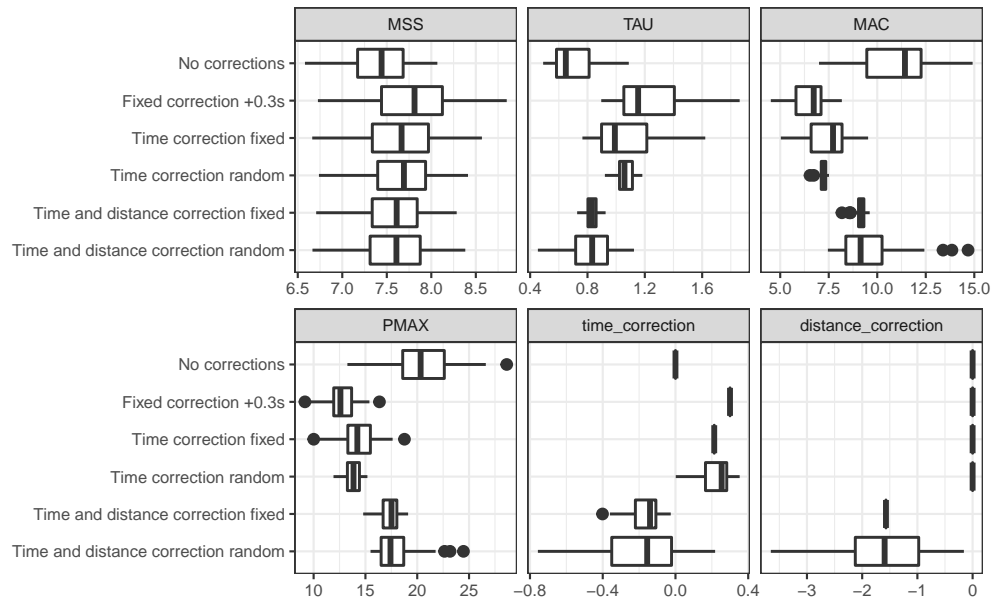
383 The following models were used: (1) no corrections model, (2) fixed time correction model (using  
 384 0.3s heuristic rule of thumb), (3) estimated time correction as a fixed effect model, (4) estimated time  
 385 correction as a random effect model, (5) estimated distance correction as fixed effect model (and time  
 386 correction as random effect), and (6) estimated distance correction as random effect model (please refer to  
 387 the Supplemental files for the R code).

388 The following image represents model fit estimator RSE for each model. As can be seen, RSE is  
 389 reduced the more flexible the model.



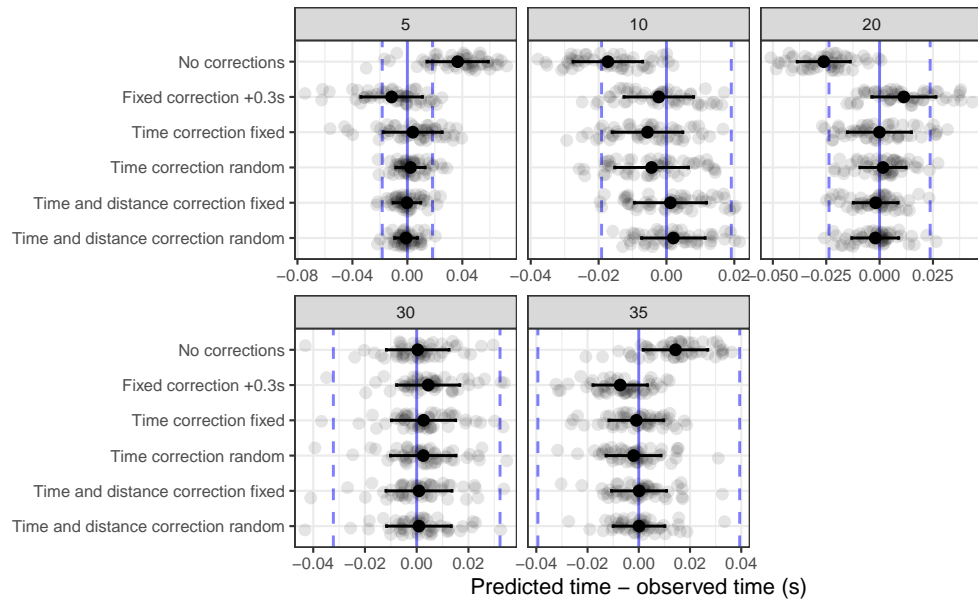
390

391 The following image depicts estimated parameters for each model:



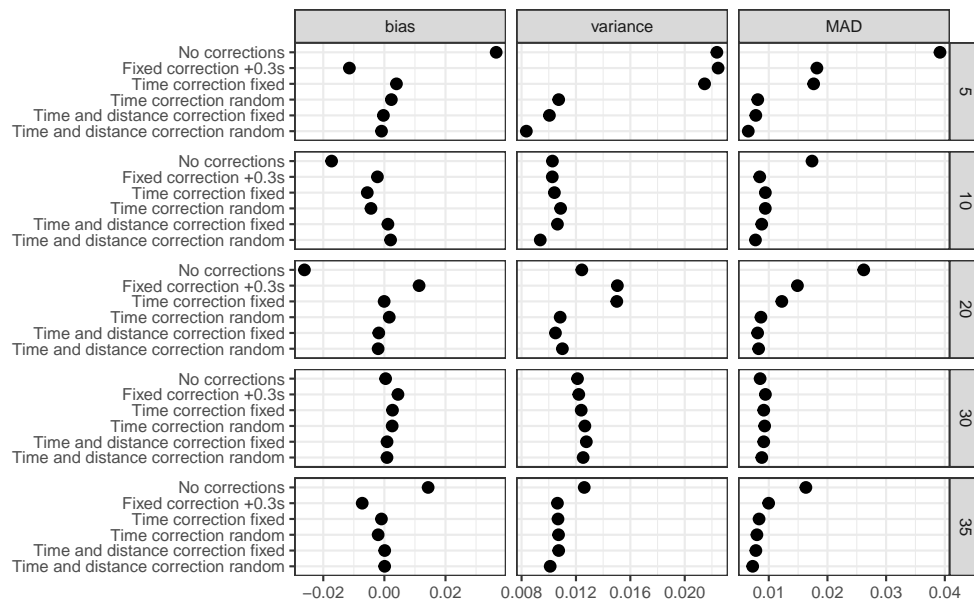
392

393 The following image depicts model residuals across distance splits. To provide practical magnitude of  
 394 the residuals, we have used between subject observed time SD multiplied with 0.2 and -0.2. This provides  
 395 practical anchor for the residual magnitude, often referred to as *smallest worthwhile change* (SWC) or  
 396 *smallest effect size of interest* (SESOI) (Jovanović 2020). If the residuals are within this magnitude band,  
 397 then the model is good in making practically useful predictions. Error bars represent residual bias  $\pm 1$  SD.



398

399 The following figure depicts model residuals estimators (bias, or mean residual; variance, or SD of  
 400 the residuals, and MAD, or mean absolute difference).



Which model should be used? Although providing a better fit (using RSE as an estimator of model fit), the time and distance correction models often estimate these parameters that are harder to interpret (e.g., negative distance correction). Although providing novel theoretical models in this paper, we acknowledge the need for validating them in practice, against gold-standard methods, assessing their agreement, as well as their power in detecting and adjusting for timing inconsistencies.

We are hoping that the **shorts** package will help fellow sports scientists and coaches in exploring short sprint profiles and help in driving research, particularly in devising measuring protocols that are sensitive enough to capture training intervention changes, but also robust enough to take into account potential sprint initiation and timing inconsistencies.

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