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# Elite North American Soccer Performance in Thermally Challenging Environments: An Explorative Approach to Tracking Outcomes

Running Head: SOCCER PLAYER PERFORMANCE AND PERCEPTIONS IN THERMALLY CHALLENGING CONDITIONS

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# Elite North American Soccer Performance in Thermally Challenging Environments: An Explorative Approach to Tracking Outcomes

Running Head: SOCCER PLAYER PERFORMANCE AND PERCEPTIONS IN THERMALLY CHALLENGING CONDITIONS

Abstract: *Aims:* The physiologic challenges related to performances in hot conditions calls for dedicated consideration when planning athlete training, although complete amelioration of the effects of heat may not be possible. We aimed to quantify within-subject correlations between different measures of environmental temperature and performance changes over multiple elite soccer competitions. *Methods:* Thirty-seven elite male soccer players (age:26 ± 3.4years, height:171 ± 2cm, body mass:78 ± 7.1kg) competed in North America over four seasons (range:3 to 98 matches). Players wore global positioning system devices during games and reported differential-RPE immediately post game. Temperatures at kick-off, week average temperature, the difference between game-day and week average ($\text{Diff}_{\text{Temp}}$), and heat index at kick-off were obtained. Within-player correlations were calculated using general linear models to quantify associations between fluctuations in temperature measures and physical and perceived outputs. *Results:* Correlations between total distance and the various temperature measures were trivial to small (range: -0.08 to 0.13, p=<0.001-0.02). Small negative correlations were found between all temperature measures except $\text{Diff}_{\text{Temp}}$ and high-speed running (HSR) (range: -0.17 to -0.14, p=<0.001). Most correlations between differential-RPE and temperature measures were trivial to small and not significant (r=0.06 to 0.18 p=0.03-0.92) although breathlessness-RPE and heat index showed a small significant association (P=0.018) *Conclusion:* Decrements in HSR appear to be associated with increased environmental temperature however, these associations are small in magnitude.

KEYWORDS: Environmental, Football, Temperature, Differential Rate of Perceived Exertion, Match, Heat Index

## INTRODUCTION

The international soccer calendar is a yearlong process, with many domestic leagues lasting nine to ten months, and then international competitions played during the remaining months. This leads to vastly differing temperature profiles during a competition dependent on location, month of the year and time of day (Chmura *et al.*, 2017). Tournaments such as the FIFA

Men’s World Cup 2022 in Qatar, FIFA Women’s World Cup 2023 in Australia and New Zealand, FIFA World Cup 2026 in the USA, Canada and Mexico and the upcoming FIFA U20 World Cup in Indonesia pose unique challenges from a game-time temperature perspective. The locations of these tournaments could result in temperature ranges which span 40-50°F (~25*C) from one city to the next (Company, 2022). The International Olympic Committee released a consensus statement calling for increased research into elite athletes and their response and management of thermal strain during competition (Bergeron *et al.*, 2012). With such varying degrees of temperature within a singular competition, preparation, performance management and recovery become important factors, with a special focus upon thermophysiology required (Periard and Racinais, 2019).

Performance in thermally challenging environments is dependent on both the external environment, and the individual’s ability to maintain homeostasis (Cheung, 2010; Periard and Racinais, 2019). Heat has been shown to affect multiple physiological systems, which can result in decrements to strength, power, speed and potentially sport specific neuromotor skill performance (Cheung, 2010; Bergeron *et al.*, 2012; Periard and Racinais, 2019; McCubbin *et al.*, 2020). Measures have been employed to assess the challenges caused by the environment. For example, heat index, wet bulb globe temperature (WBGT) index, and wind chill are measures which attempt to evaluate risk for thermal issues based on multiple external factors such as wind speed, humidity, and temperature (Bergeron *et al.*, 2012). While effective at forecasting responses, combined metrics such as those previously stated lack the context necessary to define the physiologic mechanism impacted, making practical guidance infeasible (Roghanchi and Kocsis, 2018; Thomas and Uminsky, 2022). Decision making in the applied world may need to occur at the individual metric level, to ensure interventions are applied specific to the needs of the athletes in challenging situations. In turn, decisions based upon the individual metrics may be more complex, as there are more variables to assess, and difficult to interpret due to multiple measures being considered (Roghanchi and Kocsis, 2018; Thomas and Uminsky, 2022).

A key characteristic of performance decrements in thermally challenging environments is progressing levels of dehydration resulting in reductions in cardiac stroke volume, which in turn can affect brain and muscle function, core body temperature regulation, and neurologic responses to stimuli (Bergeron *et al.*, 2012; Periard and Racinais, 2019). While acclimatization to hot environments has been proven an effective approach in multiple sporting environments (Mohr and Krustrup, 2013; Sabou *et al.*, 2020; Vanos *et al.*, 2020), this approach may not be practically applicable outside of preseason in elite soccer environments. Bergeron et al. (2012) suggests that although just a few days acclimatization can help, two weeks is needed for extreme environments. The difference between following best practices or not in this instance could double the necessary budget for travel for a team during a season and may only be applicable if the schedule allows for it. Though it should be noted that heat can serve as a benefit to some performance types, like maximal sprinting and throwing for distance (Périard and Racinais, 2014; Periard and Racinais, 2019). It is well noted that thermally challenging environments, in both the hot and cold, have specific responses from the neuromuscular, cardiovascular, endocrine systems and cognitive functions, and can be used as an additional stressor in training, allowing for supercompensation to enhance performance (Cheung, 2010; Periard and Racinais, 2019). Thus, whilst it is presumed that physical performance in soccer may be reduced in thermally challenging environment the relationship is likely more nuanced and may result in a combination of subjective and objective load measures serving to guide decision making.

In elite soccer, where acclimatization may not be an achievable option throughout a season, understanding the potential effects of competing in thermally challenging environments may be the most proactive approach to preparation for challenging thermal conditions. A data informed decision-making process can aid the discussion with all stakeholders pertaining to preserving physical outputs and optimizing performance. Additionally, information on performance outputs in thermally challenging environments may aid practitioners in managing stress throughout the training process to reduce the acute and additive stress induced by thermally challenging environments. Thus, we aimed to evaluate the effect of temperature measures on player physical and subjective outputs within an elite North American soccer competition.

## MATERIALS AND METHODS

*Experimental Approach to the Problem*

This retrospective observational study was conducted within an elite professional North American soccer team, training and competing full time, over the course of four seasons (2017 to 2020), which also included the COVID-19 tournament in a bubble location from July to August 2020 in a hot environment (McKay et al., 2022).

*Participants*

Thirty-seven professional football players from a single club (Age: 26 ± 3.4 years, Height: 171 ± 2.7cm, Body mass: 78 ± 7.1 kg) participated in this study and played 75min (95.7 ± 7.5min; 126 games) in at least one first-team match during the study period. Goalkeepers were excluded from the study. Only data from competitive matches were included. The team's home stadium is within the geographic temperate zone, between 23.5°N and 66°N latitude, and located approximately 97km from the Atlantic coast. Participant consent was obtained for all data collection and use in further research via an informed consent process, and the study was approved as part of a larger project by ***

*Informed Consent*

The athletes in this study have given written consent to the inclusion of material pertaining to themselves and acknowledge that they cannot be identified via the paper. Athletes were also informed that all of their data was anonymized prior to any analysis.

*Outcome measures (dependent variables)*

Outcome variables were chosen to provide an understanding of the physical performance outputs of the players (external load) and the relative psycho-physiological and biomechanical response to these outputs (internal load) (Impellizzeri, Marcora and Coutts, 2019; McLaren, Coutts and Impellizzeri, 2020). Global Positioning System (GPS) derived total distance and high-speed running distance were chosen to provide a broad measure of overall locomotive and high intensity locomotive performance. These locomotive measures have been shown responsive to previous stressors, and aligned with changes in internal load measures for a given workload, allowing for further assessment of additional stresses caused by the environmental temperature (Gallo *et al.*, 2016; Mohammed Ihsan *et al.*, 2017; Thorpe *et al.*, 2017). To account for differences in playing minutes between players these values were divided by player duration and analysed as meters per minute. Ratings of perceived exertion (RPE) were chosen to represent the internal training load. Session RPE (sRPE) has been shown to be a valid measure of internal training load sensitive to differences in external load and associated with physiological markers such as Heart Rate, percentage VO2max, muscle electrical activity, blood lactate and respiration rates (Chen, Fan and Moe, 2002; Lea *et al.*, 2022). Due to the explorative nature of this paper, and that different types of thermally challenging environments impact physiological systems specifically (Cheung, 2010; Périard and Racinais, 2014; Periard and Racinais, 2019), we chose to also differentiate the RPE response into cardio-respiratory (breathlessness exertion), neuromuscular (leg exertion) and cognitive exertion. Differential RPE (dRPE) has shown sensitivity to different forms of exercise and intensities (McLaren *et al.*, 2016; McLaren *et al.*, 2017), while also showing variations based on differing environmental contexts (Young, Cymerman and Pandolf, 1982). Ultimately, these measures are potentially useful in team sports and capable of differentiating between sessions with known physiological differences (Mclaren *et al.*, 2016; McLaren, , *et al.*, 2017; Wright *et al.*, 2020).

*Procedures*

Data collection processes for Global Positioning System (GPS) were undertaken in line with Draper et al. (2021). In addition to the outcomes measured by Draper et al. (2021), differential Ratings of Perceived Exertion (dRPE) were measured on the CR-100 scale (Borg and Borg, 2002) after the match to assess athlete's subjective perception of the effort over the match. Players reported cardiorespiratory (breathlessness) and neuromuscular (leg) exertion (Borg *et al.*, 2010; Mclaren *et al.*, 2016). dRPE surveys were completed via personalized messages on player's mobile electronic devices and social media communications (Facebook messenger) to simplify the data collection process for both players and researchers, limiting the time taken to complete the survey (Noon *et al.*, 2015; Draper *et al.*, 2021). Surveys were automatically sent out to players after games, approximately 2hrs after kickoff. When completing the survey, the scale (CR-100) was shown prior to each question, and anchors were stated within each question to give players reference to the scale again (Draper et al., 2021). This survey was typically completed within 2 hours of the session or match.

In this exploratory study, the intent was to study measures which might help practitioners better explain the impact that temperature, temperature changes or humidity may have on real performance conditions in elite soccer. Wet Bulb Globe Thermometer (WGBT) readings are known as the gold standard for measuring thermal stress in the field (Racinais *et al.*, 2015; Gibson *et al.*, 2020), though this data is not always readily available or practically viable for use in decision making on game days. For the purposes of this research, retroactive data was collected and as such, WGBT data was not available. Data relating to environmental conditions were collected from publicly-available weather data (*Weather Underground*, 2022). Each day, staff at the club collected information relating to the weather conditions in their home city, or in the city where the team's soccer activity was conducted in the case of "away" match preparation, game times ranged from 1:00pm to 8:00pm. This data typically included a time of day, which was selected based on the reported time of kickoff on the league website or training time based on the team's monthly calendar. The closest time frame for the weather report to the reported team start time was selected when there was not an exact match. Variables on the weather website included temperature, dew point, humidity, wind, wind speed, wind gust, pressure, precipitation, and subjective condition. For the purposes of the current study, temperature and humidity were captured in the dataset. From these, four metrics were derived as potential predictors, kick off temperature, average weekly temperature, temperature difference, and kick off heat index. Kick off temperature is the ambient temperature at the start of the game. Average weekly temperature, is the average of reported temperatures for the 7 days prior to game day. Temperature difference is the difference between the kick-off temperature and the average weekly temperature. Temperature difference was setup so that positive values represent Kick Off Temperature being the higher value and negative values represent Average Weekly Temperature being the higher value. Heat Index, which is a value to represent what the temperature "feels like" to the human body when relative humidity is combined with air temperature, was calculated using the National Weather Service's reported equation (Weather.gov, no date), taking into account the ambient temperature and relative humidity from the game day weather report.

### *Statistical Analysis*

To quantify within-player correlations between independent temperature-related and dependent / outcome variables, a general linear modelling approach (GLM) was used (Bland and Altman, 1995, 1996; Bakdash and Marusich, 2017). Following visual inspection of the dRPE residuals, we suspected some departure from normality and therefore ran the models after log-transformation of data. For dRPE values, the external load measure of total distance, and log-transformed results, were added to the model as a covariate to glean more information about the causal pathway between temperature and dRPE, helping to address the question of whether within-subject changes in temperature are associated with changes in dRPE, independently from any influence of changes in external load. The transformed and non-transformed data were compared as a sensitivity analyses. Based on the visual inspection of the histograms, the log-transformed model showed a more normal distribution of residuals, and as such, this model was selected for analysis. The following thresholds were used to interpret the magnitude of the within-subject correlation between variables: <.1 Trivial, .1 to .3 Small, .3 to .5 Moderate, .5 to .7 Large, .7 to .9 Very Large, and .9 to 1.0 Almost Perfect (Hopkins, 2004). All results are shown with 95% confidence intervals. The statistical analysis software, SPSS (SPSS Inc., Chicago, IL, USA) was used for the statistical calculations.

## RESULTS

Descriptive data for outcome measures are presented in Table 1, descriptive data for predictive measures are presented in Table 2. Within-player associations between the four predictive thermal-related variables and external load are presented as correlation coefficients with 95% confidence intervals in Figure 1, for RPE measures in figure 3. An example of individual within-player associations between $KO_{temp}$ and HSR distance is presented in Figure 2.

[Table 1 ABOUT HERE]

[Table 2 AOUT HERE]

Small negative correlations were observed between HSR and $KO_{temp}$ (r= -0.14, -0.208 to -0.076), HSR and $Week_{temp}$ (r= -0.15, -0.210 to -0.077), HSR and $KO_{HeatIndex}$ (r= -0.17, -0.239 to -0.108), TD and $KO_{temp}$ (r= -0.12, -0.187 to -0.054) and TD and $KO_{HeatIndex}$ (r= -0.13, -0.198 to -0.66) (figure 1), with all other correlations reported in Figure 1. We obtained 882 data points for the external load variables. Perceptual ratings (figure 2), which were based on 193 data points in the analysis, had mostly trivial to small positive correlations, with all $Diff_{Temp}$ outcomes and dRPE-Tech* $KO_{temp}$ resulting in non-significant findings (p=0.06 to 0.94). An example of the observed between-player heterogeneity in slopes and intercepts is presented in figure 3 for HSR and $KO_{temp}$.

[FIGURE 1 ABOUT HERE]

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

## DISCUSSION

Competing in thermally challenging environments is commonplace in elite North American soccer. We aimed to understand the association between temperature measures and physical performance metrics in competition, where acclimatization may not be achievable. We observed small negative associations between HSR and multiple temperature measures, and between total distance kick of temperature and heat index. We also observed a small positive correlation between breathlessness-RPE and heat index but all other associations between temperature measures and d-RPE were unclear. Thus, a novel finding of this study was that HSR distance appears to reduce as temperature measures increase and this may be accompanied with an increase in breathlessness-RPE. However, the magnitude of these associations are small.

The interpretation of changes in in-game physical outputs is a complex practice, though has important implications for decision-making within the elite soccer environment (Bradley and Nassis, 2015). Any trivial to small change in outputs associated with a single predictive measure are likely due to match running performance being multi-factorial in nature (Bradley and Nassis, 2015). In previous literature, temperature has been evaluated as a potential contextual variable which could have an effect on soccer performance (Draper *et al.*, 2022). The current analysis found total distance had a small negative correlation with $KO_{temp}$ and $KO_{HeatIndex}$, and trivial, negative correlations with $Week_{temp}$, $Diff_{Temp}$. This is not completely unexpected as Draper et al. (2022) reported heterogenous effects for heat on total distance with correlation coefficients ranging from trivial (-0.14 to moderate (-0.96) in a recent systematic review. The population sizes, population makeup and temperature ranges of the experimental groups were likely major determinants of the calculated correlation coefficients. Based on the slopes of our models for $KO_{temp}$, $Week_{temp}$, $Diff_{Temp}$, $KO_{HeatIndex}$ ($\beta$=-0.21, -0.35, -0.17, -0.18, respectively) it could be expected that with a 10°C increase in temperature, there would be a change in total distance of -185m, -150m, -311m and -160m, respectively, if a player played 90 minutes, but due to the wide confidence intervals any attempt of using these values for prediction purposes would be imprecise. Based on this notion, only the change in total distance at the far extremes of temperatures would fall outside of the typical error measurement percentage (TEM%) of GPS units, 1.3% for total distance (Johnston *et al.*, 2014) and thus likely to be more than just measurement noise (Buchheit, Rabbani and Beigi, 2014; Schneider *et al.*, 2018).

The current study found that $KO_{temp}$, $Week_{temp}$ and $KO_{HeatIndex}$ showed a statistically significant small negative correlation with HSR, a key predictor of scoring chances in elite soccer (Wallace and Norton, 2014; Williams *et al.*, 2017; Dalen *et al.*, 2019). The effect of environmental factors such as temperature on high-speed running in elite soccer players is not clear in the literature with studies reporting a range of effects from large negative (d= - 0.98) to large positive effects (d=1.30) (Draper et al., 2020). Some research indicates that athletes themselves control outputs through pacing strategies which may impact the statistical value of such analyses (Carling and Dupont, 2011; Dellal *et al.*, 2013; Julian, Page and Harper, 2021). The small but significant correlations we observed may reflect HSR being better able to detect physiologic and residual fatigue, as noted previously, though these responses remain individualized (Figure 3) (Hader *et al.*, 2019). Here the slopes of the models (β=-0.03, -0.04, -0.01, -0.03 respectively) suggest that with a 10°C increase in temperature we could expect to see a -30m, -32m, -11, -29m, change in HSR, if the player played 90 minutes, which is more than the expected measurement noise (Johnston *et al.*, 2014). With just a ±10% fluctuation in humidity, and the same temperatures, risk ranges can shift from "Caution" to "Danger" zones in heat index and WGBT ), representing greater physiologic impact and greater health risk involved with performing in these environments. Our data supports the work by governing bodies to enact governance surrounding thermal stress ranges to find solutions and create rule changes to promote athlete health and safety and maintain a minimal standard for matches.

Within the current analysis, it should be unsurprising that external load variables and the perceptual measures of load result in very similar magnitudes of correlation, mostly trivial to small. These measures have been found to be mode dependent and are correlated between themselves (Young, Cymerman and Pandolf, 1982; Mclaren *et al.*, 2016). dRPE values were found to be helpful measures to monitor internal load, aid in the prescription of exercise, enhance precision of measurement, and differentiate between types of load in athletes (Mclaren *et al.*, 2016; McLaren, *et al.*, 2017; McLaren, *et al.*, 2017; Barrett *et al.*, 2018). It was expected to observe RPE measures increase within this study, as heat is shown to impact the physiologic systems, specifically the cardiovascular and endocrine systems (Brutsaert *et al.*, 2000; McLaren, Smith, *et al.*, 2017; Wright *et al.*, 2020). Increases in breathlessness RPE were associated with increased heat index but the association was small and likely not practically important. Analysis of the slopes suggest a 10°C increase in heat index would be associated with on 2 unit change in breathlessness RPE, considerably less than the minimally important change of 8 arbitrary units on the CR-100 scale proposed by Wright et al., (2020). That said, individual slopes varied within their responses to environmental temperatures so this does not rule out substantial increases in exertion in individual players. As such, there is a potential benefit of tracking dRPE when heading into times of persistently challenging temperatures, like those encountered in the southern United States daily in the months of June, July and August as it may identified smaller physiologic changes in stress response.

Conducting research in an applied world is challenging (Bishop, 2008; Coutts, 2016), and there were some inevitable limitations to this work. Firstly, we did not control for fixture congestion within this study as this would compromise the useable data set but could have contributed to variation in load measures. Matches where players were given red cards, and a team played down a man and lopsided results (>5 goal difference between teams) were eliminated to reduce the error inside of the selected matches. Furthermore, WGBT data was not available for analysis, though it is acknowledged that this data is the preferred measure in assessing thermal challenge during matches. Though, part of the purpose of this study was to identify measures which could be utilized proactively in managing stressors incurred by athletes and be useful at the applied level as discussed in workplace safety frequently (Roghanchi and Kocsis, 2018). Finally, we did not control for strategies to reduce thermal effects such as hydration strategies or halftime thermal management. Players and staff performed their normal activities and performance interventions. As is the case in a team sport environment compliance with these factors were not consistent across all the population, and as such were not controlled for. The aim of this study however, was to quantify the relationship between thermal metrics and physical performance in a “real world” setting and thus controlling for such factors would not represent normal practice.

## *Conclusion*

Thermally challenging environments are part of a range of unique challenges while competing in North American professional soccer. We observed increases in thermal metrics, such as heat index, were associated with decreases in high-speed running and increases in breathlessness-RPE. However, these associations were small in magnitude.

## Practical Applications

High-speed running and breathlessness-RPE seems to be associated with changes in thermal conditions and could be important metrics to consider in data-based decision making in real time. Particularly as these associations maybe differ between individuals.

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## DECLARATION OF INTERESTS

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 1. Outcome Measure Descriptive Statistics

| Metric | Mean ± Standard Deviation | Range |
|---|---|---|
| *External Load Variables* | | |
| Total Distance (m) | 9808 ± 1439 | 7012-17820 |
| HSR (m) | 539 ± 206 | 0-1465 |
| *Perceptual Metrics* | | |
| dRPE-Legs | 83.4 ± 12.7 | 40-100 |
| dRPE-Lungs | 81.8 ± 13.6 | 40-100 |
| dRPE-Tech | 82.3 ± 14.0 | 10-100 |
| dRPE-Session | 83.2 ± 13.3 | 40-100 |
| *Next Day Athlete Reported Outcomes* | | |
| Soreness | 6.73 ± 1.12 | 5-10 |
| Mood | 8.46 ± 1.27 | 7-10 |

Table 2. Predictive Metric Descriptive Statistics

| Metric | Mean ± Standard Deviation | Range |
|---|---|---|
| $KO_{temp}$ | 20.29 ± 7.46 | -0.61 - 35.6 |
| $Week_{temp}$ | 20.5 ± 7.07 | -0.61 - 35.6 |
| $Diff_{Temp}$ | -0.19 ± 2.99 | -8.89 - 13.3 |
| $KO_{HeatIndex}$ | 20.3 ± 9.36 | 0.61 - 41.1 |

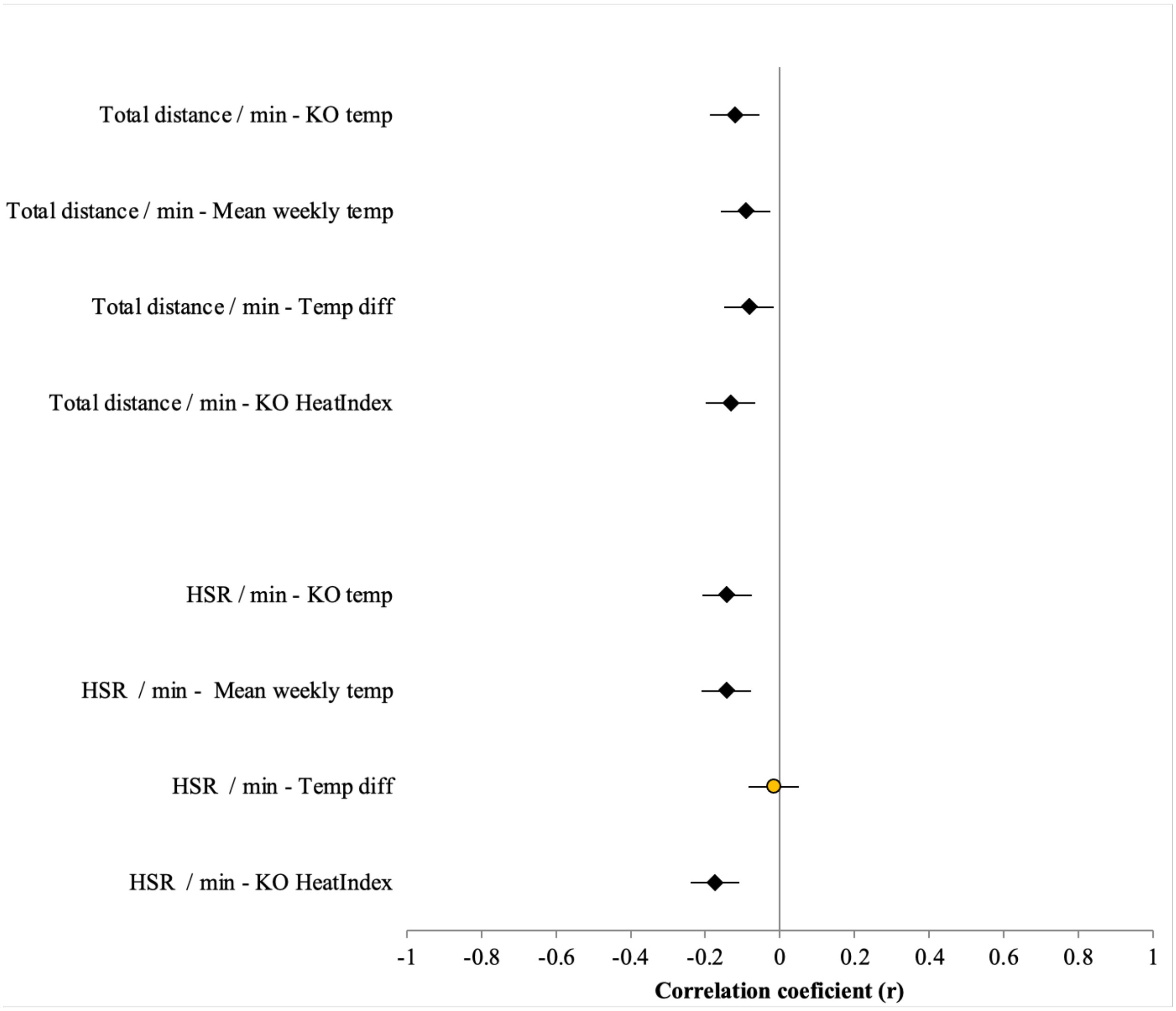

Figure 1: Within player correlations between changes in thermal variables and external load variables, error bars representing 95% confidence intervals. Statistically significant correlations, where the 95% confidence interval does not overlap zero, are indicated by black diamond markers.

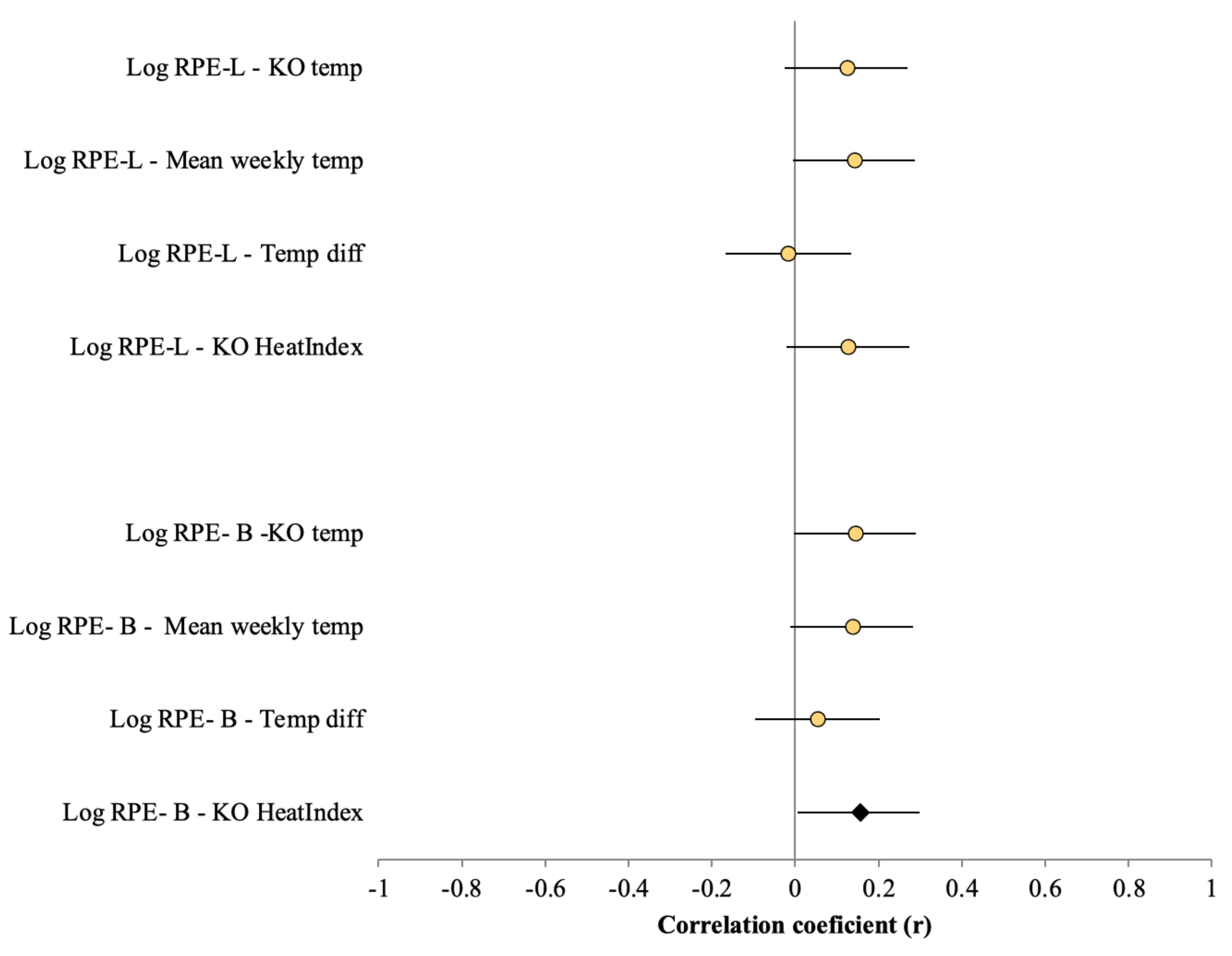

Figure 2: Within player correlations between changes in thermal variables and log-transformed RPE load variables, error bars representing 95% confidence intervals. Statistically significant correlations, where the 95% confidence interval does not overlap zero, are indicated by black diamond markers.

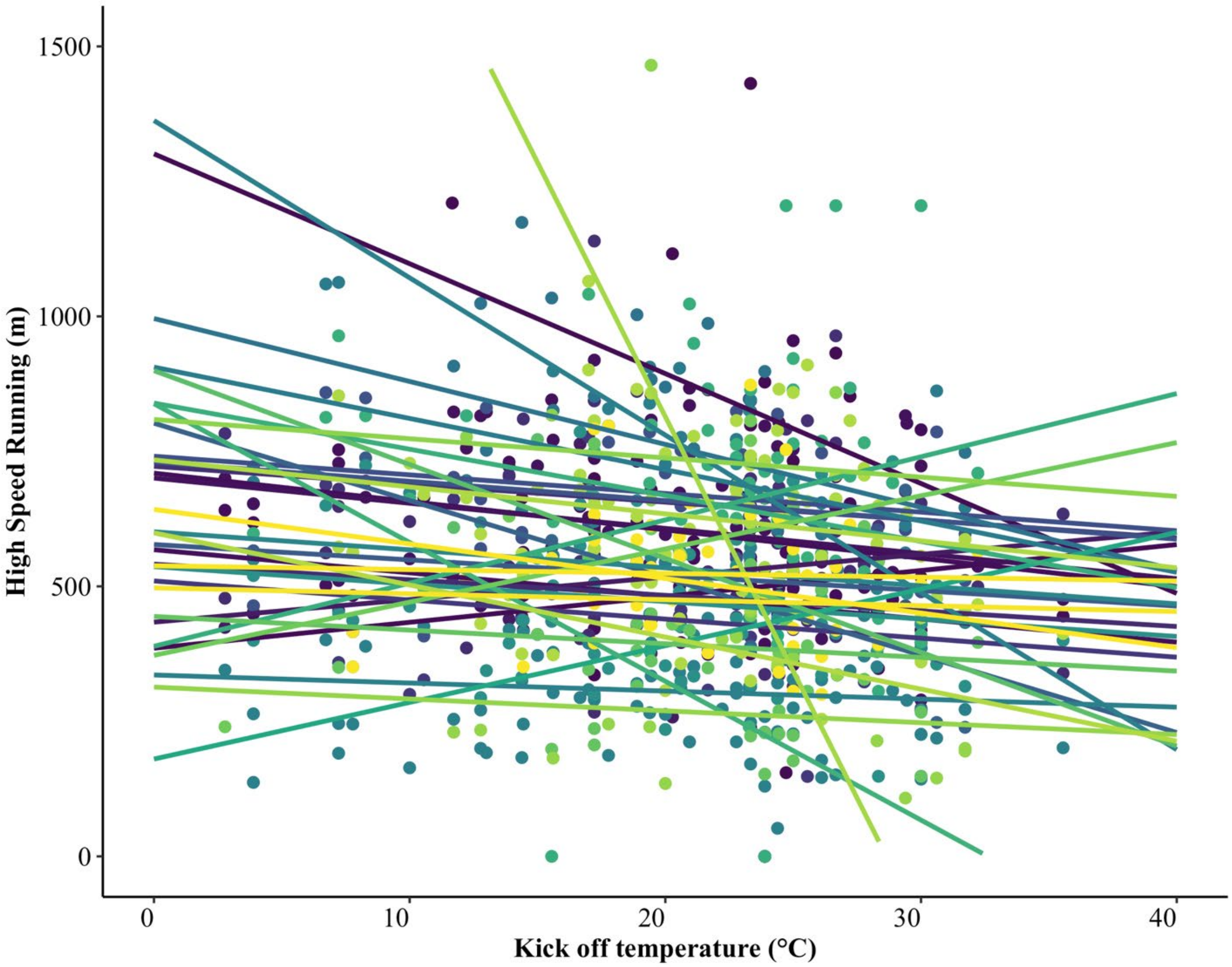

Figure 3: Individual within-player regression slopes between kick-off temperature and high-speed running distance.

## Figure Captions

Figure 1: Within player correlations between changes in thermal variables and external load variables, error bars representing 95% confidence intervals. Statistically significant correlations, where the 95% confidence interval does not overlap zero, are indicated by black diamond markers.

Figure 2: Within player correlations between changes in thermal variables and log-transformed RPE load variables, error bars representing 95% confidence intervals. Statistically significant correlations, where the 95% confidence interval does not overlap zero, are indicated by black diamond markers.

Figure 3: Individual within-player regression slopes between kick-off temperature and high-speed running distance.