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Comparative evaluation of wearable devices for measuring elevation gain in mountain physical activities

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Abstract

The aim of this article is to examine the validity of elevation gain measures in mountain activities, such as hiking and mountain running, using different wearable devices and post-processing procedures. In particular, a total of 202 efforts were recorded and evaluated using three standard devices: GPS watch, GPS watch with barometric altimeter, and smartphone. A benchmark was based on orthorectified aerial photogrammetric survey conducted by the Chilean Air Force. All devices presented considerable elevation gain measuring errors, where the barometric device consistently overestimated elevation gain, while the GPS devices consistently underestimated elevation gain. The incorporation of secondary information in the post-processing can substantially improve the elevation gain measuring accuracy independently of the device and altitude measuring technology, reducing the error from −5% to −1%. These results could help coaches and athletes correct elevation gain estimations using the proposed technique, which would serve as better estimates of physical workload in mountain physical activities.

Keywords

Mountain running, physical workload, altitude, measuring, validity, GPS, barometric device

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Introduction

Measuring the performance of an outdoor physical activity is a very complex task due to the large number of factors involved. Nowadays, mountain sport activities are becoming increasingly popular among professional and amateur athletes. As studied exhaustively by Kay,[1] the physical workload of a mountain activity will vary according to the horizontal distance covered and the elevation gain (EG). The most common estimation method for physical workload is the Naismith formula derived by Scarf,[2] which states that 1 km of horizontal effort is equivalent to 125-m EG for men and 100-m EG for women, which makes EG a key measure for estimating physical workload in mountain activities.

Mountain sport activities usually take place on mountain trails, which constantly vary in grade, terrain, and weather conditions. In this context, the speeds reported within a circuit will account not only for an individual athlete's fitness but also for the particular terrain topology.[3] In the mountains, it is common to find obstacles, such as rocks and roots, making it impossible to use standard road measuring tools like the wheel-based jones meter, which is the International Association of Athletics Federations (IAAF) standard for measuring distances in road running. Furthermore, wheel-based tools do not measure EG. Therefore, the best option for measuring outdoor circuits and activities is GPS devices.

The massification of portable devices has given athletes access to more information on their training. The errors generated by these devices can induce suboptimal strategies when planning or performing physical activities. For example, recently, Hongu et al.[4] examined the validity of energy expenditure (EE) measured using four different GPS watches. The research found that the GPS watches demonstrated lower reliability across trials for assessing overall EE when compared with a triaxial accelerometer. On the other hand, Beato et al.[5] found that GPS devices did not underestimate

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distance or peak speed when configured at 10 Hz, but standard wearable GPS devices operate at a maximum of 1 Hz.[6]

In particular, for measuring EG, studies have shown that measurements of altitude and EG differ considerably between device technology, device settings, and data post-processing methods.[7–10] Ammann et al.[6] studied the accuracy of EG measurement in GPS sport watches during road running on a 7% grade segment. They found that algorithmic procedures implemented by watch manufacturers worsened the EG estimation considerably for all brands, suggesting that standard filtering methods for road running[11] may not be appropriate for running off-road. Another study[12] showed that wearing the devices on the hip can significantly reduce the arm swing-related EG error, which can overestimate physical workload up to 5%. Some specialized sport watches include barometric altimeter, which is an alternative technology for measuring altitude under stable weather. Some studies show that unstable climates can increase the EG measuring error in barometric altimeters by fivefold, creating up to a 25% deviation from known values.[13]

On the other hand, the incorporation of secondary information in the post-processing can substantially improve the EG measuring accuracy. Menaspà et al.[8] claim that the use of the Garmin altitude correction option resulted in a 5% to 10% increase in the total EG, although there was no documented method for how this correction was conducted by the manufacturer.

The aim of this article is to examine the validity of EG measures using different wearable devices and post-processing procedures for mountain physical activities. EG is a key measure to estimating physical workload in outdoor activities, such as hiking, mountain biking, or mountain running. To the authors' knowledge, there is no published study on the validity of EG measures during physical activities in mountain settings.

Methods

Experimental approach to the problem

A retrospective observational study was performed in a well-established mountain segment (Manquehue Hill) in Santiago, Chile, consisting of 386 m of EG through 906 m of horizontal distance. These measures were obtained from an orthorectified aerial photogrammetric survey, conducted in Santiago, Chile, in 2004 by the Chilean Aero Photogrammetric Service (www.saf.cl/), a subsidiary of the Chilean Air Force. The course is free of trees or other signal obstructions and has an average grade of 42%, increasing by six times the maximum grade covered by previous EG estimation studies.

The data were registered by the authors on 202 different efforts, recorded in 116 unique field activities between 8 December 2014 and 27 July 2019. In each effort, a unique GPS trajectory was recorded with the following data obtained for each trajectory reading: coordinate pairs, timestamps, and raw altitude estimation. Sometimes, more than one effort was recorded on the same day. In total, 84 climbs and 118 descents were recorded, and the total time spent covering the route ranged from 8.9 to 55.6 min, with a mean of 20 min. There is a difference between the number of ascents and descents because 34 activities were recorded climbing the hill through an alternative route and descending through the analyzed segment.

A total of three different devices were used: (a) Smartphone with GPS (iPhone 6SE), (b) GPS watch (Garmin Forerunner 225), and (c) GPS watch with barometric altimeter (Garmin Fenix 5). The GPS watch with barometric altimeter is the most developed of the studied devices, being released in 2017. This device was used for all efforts measured in this study during 2019. Specifically, 65 efforts recorded with the smartphone, which was worn 23% of the time on the hip and the rest of the times on the arm, 114 efforts recorded with the GPS watch, and 23 efforts recorded with the GPS watch with barometric altimeter.

The variance in device settings resulted in a number of readings during an effort, ranging from 65 to 636. During 8.9% of the efforts, the "ultra-saving" mode was used to record the data, which uses low sampling recording to optimize battery life, a common setting in ultra-running activities.

GPS tracking software measures the total EG of an effort by calculating the EG between every two readings and then adding these, and does the same for estimating horizontal distance. These EG and distance calculations were applied for every effort recorded for all devices. Finally, speed was calculated by dividing horizontal distance by time difference.

The percentage error of each effort's horizontal distance and EG was then calculated relative to the benchmark measure. Percentage error was used instead of absolute percentage error since the error sign is also a variable of interest in this study.

Data were enriched with weather information after the gathering process. Hourly historical weather data for Santiago, Chile, were obtained from Apixu (Apixu.com) with the following ranges: temperatures 5.1 °C–30.8 °C, humidity 11%–75%, precipitation 0 and 15 mm, and daylight and cloud presence between 0 and 1.

Description of all the variables is presented in Table 1, and descriptive statistics are presented as quartiles, mean, and standard deviation in Table 2.

Statistical procedures

Two different statistical approaches were carried out. First, an analysis of the descriptive statistics of EG and horizontal distance errors was conducted. Within this approach, a distributional analysis of errors was conducted. As part of this process, the coefficient of variation of the errors for every device under research was

Table 1. Variable descriptions.

Variable	Description
Distance	Horizontal distance in meters
EG	Elevation gain in meters
Distance error	Percentage horizontal distance error versus benchmark
EG error	Percentage EG error versus benchmark
Up or down	1 if effort was uphill, 0 if downhill
Readings	# of GPS readings for that effort
Arm swing	1 if device was worn on arm, 0 if not
Barometer	1 if device measures elevation with barometer, 0 if GPS
Smartphone	1 if was smartphone, 0 if wrist watch
Is day	1 if day, 0 if night
Cloud	Cloud cover as percentage
Precipitation	Precipitation amount in millimeters
Speed	Horizontal distance over time
Humidity	Humidity as percentage
Temp	Temperature in Celsius
Average distance	Horizontal distance between readings
Ultra-saving	1 if ultra-saving setting, 0 if normal

EG: elevation gain.

calculated. Second, following Ammann et al.,[6] linear regression models were performed to measure the determinants of EG and horizontal distance estimation errors. The aim was to relate the dependent variables, distance error, and EG error, with the following independent variables: device type (smartphone, GPS, or barometer), arm swing (yes or no), speed, weather conditions (humidity, cloud, precipitation, and temperature), daylight, average distance between readings, and battery-saving option (yes or no). After performing this regression, the variables without statistically significant coefficients were removed, and a second regression was performed, only with the selected variables, expecting to maintain explanatory power while simplifying the model.

Before performing the regression, a correlation analysis was done to the independent variables to understand if linear model assumptions were being met. In case of highly correlated variables, the redundant variable were dropped, maintaining the variable that accounted for the maximum explanatory power. Finally, ordinary least squares (OLS) regression was performed with the resulting independent variables.

Post-processing procedures

In addition to studying the accuracy in raw EG, the EG was measured after applying two different post-processing procedures, an algorithmic approach and an altitude correction approach with an external source, following previous studies.[6,8]

Most sports tracking software applies smoothing algorithms for correcting GPS trajectories,[11] but manufacturers do not disclose their filtering algorithms. For this study, the filtering algorithms described by Schuessler and Axhausen[11] were implemented, using a Gaussian kernel. For each coordinate dimension, the smoothed value at each time was computed using a kernel bandwidth of 10 s, and then the EG and horizontal distance over smoothed coordinates was calculated.

For altitude correction with external sources, a locally enhanced digital elevation model (DEM) based on NASA's Shuttle Radar Topography Mission (SRTM) data was used, which is available for anybody to use at Amazon Web Services (https://registry.opendata.aws/terrain-tiles/). The SRTM data were also used by previous studies[9] for altitude reference in road cycling EG estimation. The DEM returns an altitude value for any given latitude and longitude, so this DEM altitude value was calculated for every coordinate pair recorded in the present study, and then EG and EG error was computed.

Table 2. Descriptive statistics of numeric variables.

	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum	Standard deviation
Distance (m)	685	886	897	886	913	948	53
EG (m)	276	357	359	366	376	402	16
Up or down (bin)	0.00	0.00	0.00	0.41	1.00	1.00	0.99
Readings (#)	65	123	172	203	283	636	112
Arm swing (bin)	0.00	1.00	1.00	0.77	1.00	1.00	0.42
Barometer (bin)	0.00	0.00	0.00	0.11	0.00	1.00	0.31
Smartphone (bin)	0.00	0.00	0.00	0.30	1.00	1.00	0.46
Is day (bin)	0.00	0.00	1.00	0.72	1.00	1.00	0.44
Cloud (%)	0	0	2	12	12	100	23
Precipitation (mm)	0.00	0.00	0.00	0.08	0.00	9.46	0.79
Speed (m/s)	0.26	0.60	0.75	0.84	1.16	1.69	0.32
Humidity (%)	11	22	29	33	42	75	14
Temp (°C)	5.1	12.4	16.0	16.2	20.0	30.8	5.5
Average distance (m)	1.3	3.1	5.4	5.7	7.4	13.6	2.9
Ultra-saving (bin)	0.00	0.00	0.00	0.09	0.00	1.00	0.28

EG: elevation gain.
The expression (bin) stands for binary variables (1 if yes or 0 if no).

Table 3. Descriptive statistics of EG, distance, EG error, and distance error.

Variable	Device	Mean	Standard deviation	Minimum	Maximum	Coefficient of variation (%)
EG (m)	Smartphone	359	18	265	387	5
	GPS watch w/barometer	396	4	384	402	1
	Standard GPS watch	363	11	330	386	3
EG error (%)	Smartphone	−7%	5%	−31%	0%	−69
	GPS watch w/barometer	3%	1%	−1%	4%	45
	Standard GPS watch	−6%	3%	−14%	0%	−49
Distance (m)	Smartphone	898	32	686	943	4
	GPS watch w/barometer	761	68	696	893	9
	Standard GPS watch	903	18	866	948	2
Distance error (%)	Smartphone	−1%	4%	−24%	4%	−391
	GPS watch w/barometer	−16%	7%	−23%	−2%	−46
	Standard GPS watch	0%	2%	−4%	5%	−552

EG: elevation gain.
Since error measures are defined as a percentage, then the descriptive statistics for these variables are also reflected in this unit. Coefficient of variation is calculated as the standard deviation, divided by the mean.

A fourth EG estimation was obtained by applying both processes, first applying Gaussian filtering to latitude and longitude, and then obtaining altitude from the DEM for smoothed coordinates. Therefore, four different datasets were generated, so the variance in EG estimation was analyzed with treatment-specific and device-specific box-plots.

The data gathering, processing, and statistical analysis were performed in R language, with both data and scripts freely available upon request.

Results

A total of 202 efforts of mountain hiking on a well-established trail in Santiago, Chile, were analyzed. All devices presented EG measuring errors, although the barometric device tended to overestimate EG with a mean EG error of $3 \pm 4\%$, while GPS devices tended to underestimate EG with mean values of $-6 \pm 3\%$ and $-7 \pm 4\%$ for the GPS watch and smartphone, respectively. Horizontal distance error is also reported, having a mean value of $-2 \pm 6\%$ for all devices, closer to 0 than EG error, but with higher variance.

In Table 3, the distributions of EG error and distance error by device are presented. From these distributions, it is clear that all three devices presented considerable EG measuring errors. However, in mean distance error, standard GPS and smartphones present close to zero distributions, with distance error of $0 \pm 2\%$ and $-1 \pm 4\%$, respectively. The poorest performance on distance error was by the barometric device, but this was the only device with the ultra-saving setting, lowering the resolution of the recorded trajectories (important numbers are highlighted in bold in Table 3).

Figure 1 shows that there is high correlation in the data, and several variables are identified with high values, such as up or down and speed, since the downhill speed is much higher than that in uphill. There is also a

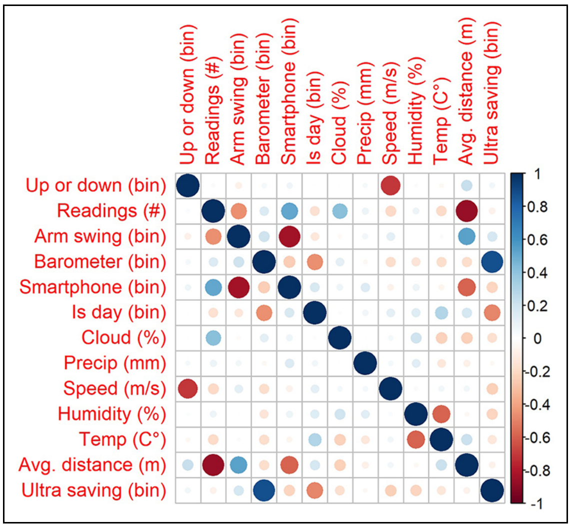

Figure 1. Independent variable correlations. The expression (bin) stands for binary variables (1 if yes or 0 if no).

strong correlation between barometer and ultra-saving, since the Garmin Fenix 5 device is the only device with a barometer and the only one that can be used in ultra-saving mode. Average distance also stands out as highly correlated with the number of readings since the first equals the segment distance divided by the latter.

For each dependent variable, EG error and distance error, two different linear models, were estimated: with all available independent variables; and only using the variables with statistically significant coefficients. The normalized coefficients for the four linear regressions are reported in Table 4, as well as regression statistics. The explanatory power of models with all variables is preserved in the models with selected variables, as can be seen in the adjusted R^2 reported at the bottom of Table 4. In EG error, this value marginally decreased from 0.55 to 0.54, while for distance error, this value

Table 4. Regression analysis results for EG error and distance error, using all available variables (all variables) and selecting only statistically significant variables (selected variables).

	EG error (%)		Distance error (%)	
Independent variable	All variables	Selected variables	All variables	Selected variables
Up or down (bin)	−0.36 (0.38)		−1.61** (0.67)	−1.25** (0.56)
Readings (#)	3.09*** (0.61)	3.05*** (0.44)	7.49*** (1.08)	5.89*** (0.53)
Arm swing (bin)	2.69*** (0.42)	2.73*** (0.41)	2.41*** (0.74)	2.73*** (0.70)
Barometer (bin)	1.00 (0.61)		−1.40 (1.09)	
Smartphone (bin)	1.76*** (0.46)	1.56*** (0.44)	2.23*** (0.83)	2.55*** (0.73)
Is day (bin)	0.39 (0.28)		0.83* (0.49)	
Cloud (%)	−0.03 (0.27)		−1.25** (0.49)	−1.44*** (0.44)
Precipitation (mm)	−0.49** (0.23)	−0.53** (0.23)	0.53 (0.41)	
Speed (m/s)	−0.02 (0.34)		−1.47** (0.61)	−1.60*** (0.58)
Humidity (%)	−0.21 (0.30)		−0.72 (0.53)	
Temp (C°)	0.06 (0.31)		−1.38** (0.56)	−0.79** (0.40)
Average distance (m)	2.42*** (0.63)	2.14*** (0.48)	1.47 (1.12)	
Ultra-saving (bin)	2.12*** (0.65)	2.76*** (0.23)	2.01* (1.15)	
Intercept	−0.05*** (0.02)	−0.54*** (0.02)	0.01 (0.05)	0.04 (0.02)
N	202	202	202	202
Adjusted R^2	0.55	0.54	0.57	0.56
F	19.5	40.2	21.1	37.3

EG: elevation gain.
For each independent variable and model, the values of standardized coefficient and standard deviation (in parentheses) are reported, along with the codes for statistical significance (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$). Sample size, adjusted R^2, and Fisher score for each model are also reported at the bottom of the table.

marginally decreased from 0.57 to 0.56. For both variables, the second model avoided spurious relations, since all selected variables are statistically significant to at least 99% confidence.

In the case of EG models, it can be seen in Table 4 that unlike horizontal distance, the intercept is statistically significant. This means that the model will always expect to have a measurement error in EG, unlike horizontal distance with a 0% error expected according to the model. The variables readings, arm swing, and smartphone were found to be statistically significant for explaining both errors, while precipitation, average distance, and ultra-saving were relevant for explaining EG error. Cloud, speed, and temperature were relevant for explaining distance error.

The number of readings presents a wide range and standard deviation as seen in Table 2, which given the fractal nature of geographical trajectories, should influence distance measurements. This effect is also reflected in the average distance between readings. The average distance between measurements is within the mountain racing standards of 10 m for segment recording,[14] showing that this setting is not enough to minimize EG estimation error.

By applying the altitude correction method described in the "Methods" section, the EG error patterns are drastically modified, shifting the distribution closer to 0% and reducing the variance as can be seen in Figure 2. It can also be seen that by applying the smoothing algorithm, the EG errors patterns are slightly modified, reducing its variance, but the average error did not shift. When applying both methods, all devices report larger EG errors than applying only altitude correction. In the case of the Garmin Fenix with both methods, the distribution worsens atypically. This can be explained by the ultra-saving mode, only available for this device. This mode reduces the GPS sampling rate, resulting in low-resolution GPS tracks. Applying a smoothing algorithm to coordinates of a low resolution GPS track results in distorted trajectories, so the subsequent EG calculation will depend on the distorted trajectory's elevation profile.

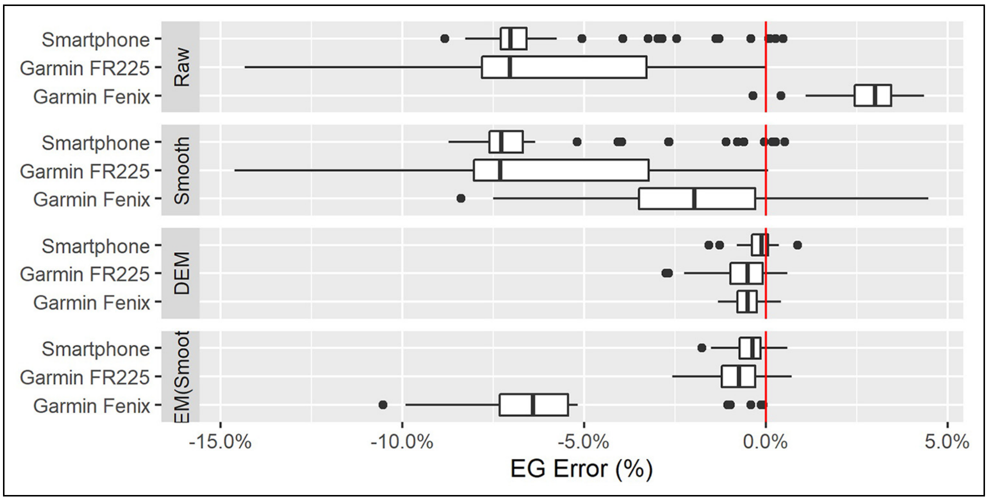

Figure 2. EG error for every device and procedure. Devices analyzed were a smartphone, a Garmin Forerunner 225 GPS Watch (FR225), and Garmin Fenix 5S GPS Watch. The different procedures tested were Gaussian smoothing, digital elevation model (DEM), Gaussian smoothing and DEM, and the raw EG measurement error.

EG errors with altitude correction fluctuate around 0, so it can be assumed that the source of the DEM, based on the SRTM, is a source of elevation that closely resembles the actual elevations in absence of signal obstructions.

EG measuring error in a mountain setting can be drastically reduced by applying an altitude correction approach. Altitude correction generates consistent estimation through all devices in this study, despite the measuring technology.

Discussion

This study determined the accuracy of devices and procedures typically used for EG measuring and estimation in mountain running.

In general, considering raw measures of EG, specialized barometric devices showed the most accurate EG reading, as was expected. On the other hand, GPS devices are more ubiquitous, but reported EG error magnitude up to 15%. For a GPS device to deliver quality elevation measurements, some conditions must be met, like clear view to at least four satellites,[15] while a barometric altimeter just requires stable weather.

The study showed that measurement errors from both types of technology can be mitigated through post-processing procedures. Altitude correction was found to be the best data procedure in reducing the EG error, allowing low-cost GPS devices to obtain similar quality in EG estimation compared to the more expensive and sophisticated barometric devices. Previous studies found that EG differs considerably between devices[8,12] and that non-disclosed altitude correction reduces the variance of EG measures in road cycling. Commercial applications, like Garmin Connect or Strava, correct altitude based on a proprietary DEM, so EG measures will differ depending on the application on which the data were processed. The main value of using an open-source DEM is that estimates can be homologated and compared across devices.

Ammann et al.[12] state that a 5% error in EG has significant impact on mountain running workload. Mean EG errors reported in this study, averaging 5%, are in line with published results for road cycling[13] and road running.[6] This magnitude suggests that altitude correction procedure should always be applied to avoid suboptimal strategies when planning or performing physical activities in the mountains.

The total EG error of a GPS track results from the sum of each segment EG bias, and this segment EG bias between two consecutive readings is affected by several factors, such as weather or the relative position of the device.[6,8,12,13] A recent study[6] found that wet conditions considerably heightened EG error to 25%, which is consistent with the results of the best model for EG error, where precipitation and humidity were found to be statistically significant variables for estimating EG and horizontal distance within the dataset, as can be seen in Table 4. This suggests that weather conditions affect not only the vertical component of physical workload estimation but also the horizontal component. Given the nature of the present study, some of the conclusions are irreproducible, so further research should validate these results with larger datasets.

In Table 4, arm swing is found to be statistically significant for EG estimation, as was anticipated,[12] and also had an effect on horizontal distance estimation. These statistically significant variables should be taken into further consideration when defining recording protocols for registering mountain circuits with portable devices.

The EG error is estimated upon the measured location and, therefore, also depends on location measuring accuracy.[7] Studying position accuracy in a mountain setting requires a different experimental design, so further research will address this issue for the available devices.

In mountain pedestrianism, unlike road, track, or treadmill settings, there is a great variation in stride and angle of foot strike with every step, so additional information about the terrain could explain the errors unaccounted for by the present study.

Applying the described smoothing algorithm decreases the accuracy of the results, as anticipated by a previous study.[13] Future research should consider testing different filtering algorithms to see if any algorithmic approach outperforms altitude correction methods.

Another important limitation of this study is that only three types of devices were tested. Other devices may exhibit different EG error patterns and the continuous development of wearable technology will require updating results in the future.

None of the existing studies focus on identifying the optimal scale for EG analysis. Since the selected DEM provides a detailed source of information with a reasonable degree of accuracy, further studies will focus on comparing the accuracy for different section lengths of mountain trail.

To engage in safer physical activities, it is essential for mountain athletes to have the best information available, including the correct horizontal distances and EG. Poor or inaccurate information could generate risks to both the performance, as well as the integrity of the athletes' achievements. This is especially true for countries such as Chile, where mountain sports activities are an important part of the population's physical activity with 64% of the national territory covered by mountains.

Conclusion

Raw and post-processed estimations of EG were compared to the reference data to understand EG estimation error and how to mitigate this error while planning or performing physical activities in a mountain setting. Given the relative ease of correcting wearable device altitude readings with DEM values, this procedure is the best practice to obtain across-device consistent measures of EG.

These results will help coaches and athletes to access quality and consistent measures of EG, allowing for more accurate estimates of physical workload in mountain activities, independent of the recording device technology. These results will also help portable device manufacturers, so they can determine more effective ways to obtain quality EG measures.

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References

1. Kay A. Pace and critical gradient for hill runners: an analysis of race records. *J Quant Anal Sport* 2012; 8(4): 1–19.
2. Scarf P. Route choice in mountain navigation, Naismith's rule, and the equivalence of distance and climb. *J Sport Sci* 2007; 25(6): 719–726.
3. Pryor JL, Adams WM, Huggins RA, et al. Pacing strategy of a full Ironman overall female winner on a course with major elevation changes. *J Strength Cond Res* 2018; 32(11): 3080–3087.
4. Hongu N, Orr BJ, Roe DJ, et al. Global positioning system watches for estimating energy expenditure. *J Strength Cond Res* 2013; 27(11): 3216–3220.
5. Beato M, Devereux G and Stiff A. Validity and reliability of global positioning system units (STATSports Viper) for measuring distance and peak speed in sports. *J Strength Cond Res* 2018; 32(10): 2831–2837.
6. Ammann R, Taube W, Kummer F, et al. Accuracy of elevation recording using sport watches while walking and running on hilly and flat terrain. *Sport Eng* 2016; 19(4): 283–287.
7. Bauer C. On the (in-) accuracy of GPS measures of smartphones: a study of running tracking applications. In: *Proceedings of international conference on advances in mobile computing & multimedia*, Vienna, 2–4 December 2013, p. 335. New York: ACM.
8. Menaspà P, Impellizzeri FM, Haakonssen EC, et al. Consistency of commercial devices for measuring elevation gain. *Int J Sport Physiol Perform* 2014; 9(5): 884–886.
9. Shen L and Stopher PR. Review of GPS travel survey and GPS data-processing methods. *Transport Rev* 2014; 34(3): 316–334.
10. Wing MG and Frank J. Vertical measurement accuracy and reliability of mappinggrade GPS receivers. *Comput Electron Agr* 2011; 78(2): 188–194.
11. Schuessler N and Axhausen KW. Processing raw data from global positioning systems without additional information. *Transport Res Rec* 2009; 2105(1): 28–36.

12. Ammann R, Taube W, Neuhaus M, et al. The influence of the gaitrelated arm swing on elevation gain measured by sport watches. *J Hum Kinet* 2016; 51(1): 53–60.
13. Mensaspa P, Haakonssen E, Sharma A, et al. Accuracy in measurement of elevation gain in road cycling. *J Sci Cycling* 2016; 5(1): 10–12.
14. ITRA. How to measure a race, 2019, https://itra.run/content/measuring-tools (accessed 22 April 2020).
15. Krause LO. A direct solution to GPS-type navigation equations. *IEEE Trans Aerosp Electron Syst* 1987(2): 225–232.