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Is GPS telemetry location error screening beneficial?

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The accuracy of global positioning system (GPS) locations obtained from study animals tagged with GPS monitoring devices has been a concern as to the degree it influences assessments of movement patterns, space use, and resource selection estimates. Many methods have been proposed for screening data to retain the most accurate positions for analysis, based on dilution of precision (DOP) measures, and whether the position is a two dimensional or three dimensional fix. Here we further explore the utility of these measures, by testing a Telonics GEN3 GPS collar's positional accuracy across a wide range of environmental conditions. We found the relationship between location error and fix dimension and DOP metrics extremely weak ($r^2_{adj} \sim 0.01$) in our study area. Environmental factors such as topographic exposure, canopy cover, and vegetation height explained more of the variance ($r^2_{adj} = 15.08\%$). Our field testing covered sites where sky-view was so limited it affected GPS performance to the degree fix attempts failed frequently (fix success rates ranged 0.00–100.00% over 67 sites). Screening data using PDOP did not effectively reduce the location error in the remaining dataset. Removing two dimensional fixes reduced the mean location error by 10.95 meters, but also resulted in a 54.50% data reduction. Therefore screening data under the range of conditions sampled here would reduce information on animal movement with minor improvements in accuracy and potentially introduce bias towards more open terrain and vegetation.

Global positioning system (GPS) tagging of wildlife is becoming a standard practice for providing information on habitat use and animal movements, and many studies have critically assessed the data provided by GPS technology (Frair et al. 2010). Wildlife GPS collars record position dilution of precision (PDOP), along with horizontal dilution of precision (HDOP), vertical dilution of precision (VDOP), time dilution of precision (TDOP), and whether or not the position is a three dimensional (3D) or two dimensional (2D) fix based on the number of observable satellites on which the position was calculated (Telonics 2009). Though previous work has shown screening datasets can reduce location errors using this information (Moen et al. 1996, 1997, Dussault et al. 1999, D'Eon et al. 2002, D'Eon and Delparte 2005) it also may lead to large reductions of observations and introduce bias into analyses of animal locations.

Dilution of precision (DOP) measures are calculated from the geometry of the satellites used to determine a position fix and were developed as a measure of positional accuracy based on trilateration, the process of determining absolute or relative locations of points using distances and geometry of hyperbolas (Langley 1999). When satellites are well-spaced across the sky, values of DOP are low, whereas clustered or linear arrangements of satellites results in high DOP values (Kaplan and Hegarty 2005). $PDOP^2$ is equivalent to $HDOP^2$ (error in the horizontal plane, x and y) plus $VDOP^2$ (error in the vertical plane or elevation/height). The more observable satellites, the better (lower) the value of DOP will be, and the greater the chances are of acquiring a 3D fix. A 2D fix is calculated for the horizontal plane when three satellites are viewable and the last acquired altitude is assumed. When four or more satellites are observable, a 3D position can be calculated. In addition to the geometry and number of satellites in the sky for calculating a position, GPS receivers need the difference in time between the time the signal was sent from a satellite and received at the GPS receiver. This time difference is used to estimate the distance, or range, between the GPS satellite and the receiver based on the estimated speed of radio waves traveling through the atmosphere. Therefore clock errors, ephemeris (satellite orbit trajectory) error, multipath (reflected and diffracted signals), radiofrequency interference, and error in atmospheric correction factors also contribute to the accuracy and precision of GPS positions. Because the range is known to be an estimated distance, they are referred to as pseudoranges (Langley 1999). Pseudoranges are estimated by statistical models and standard errors are calculated for model coefficients. These standard errors are multiplied by the error estimated from the geometry of the satellites, which amplifies the pseudorange error and is the reason why the precision estimate is referred to as ‘diluted’ (Langley 1999, Kaplan and Hegarty 2005). Increases in PDOP throughout the day at a site can occur due to linear alignments of satellites and varies by hour of day due to changes in the geometry of the satellite constellations. The speed at which radio waves travel results in small clock errors having a pronounced influence on position accuracy and since radio waves are also subject to reflection and refraction (multipath) the slight delay in these signals is problematic (Langley 1999).

Studies testing performance of GPS collars have conducted field trials in conditions that do not result in high frequencies of failed fix attempts (Frair et al. 2010). The methods presented in Lewis et al. (2007) have become a popular technique to screen GPS collar data. They offer four options for data screening: removing locations that 1) have a PDOP less than ten, 2) are 2D fixes and have a PDOP greater than five, 3) are 3D fixes with a PDOP greater than ten and 2D fixes with a PDOP greater than five, and 4) all 2D fixes, regardless of PDOP value. Here we investigate these methods of data screening and discuss the implications of attempts to reduce location error and information loss. Our objectives were to identify the relationship between DOP measures, environmental conditions, and location error. We evaluate how vegetation and terrain obstruction affects location error, proportion of 3D fixes, and DOP values for a study area located in northern Arizona where we have collected GPS location data for free ranging cougars, *Puma concolor,* using Telonics GEN3 (Telonics Inc., Mesa, AZ) GPS collars.

Material and methods

Field tests

To test if environmental conditions have a relationship with GPS collar location precision and accuracy, we collected GPS positions from a stationary test collar and compared them to higher precision measurements of location. We collected data with a GEN3 Telonics (Telonics Inc., Mesa, AZ) GPS collar deployed over the course of a year at 67 random sites stratified to sample a range of vegetative and terrain characteristics (Arundel et al. 2015). Vegetation types included grasslands, shrublands, pinyon–juniper woodlands and coniferous forests, with varying canopy cover (Homer et al. 2007) and vegetation height (US Geological Survey 2011). Landforms included prairie flats, plateaus, canyons and mountainous terrain representing a broad range of sky-views measured using topographic exposure (positive openness) (Yokoyama et al. 2002, Ironside and Peters 2015).

The test collar was programmed to obtain a fix within a three minute window once every two hours and was left at a location for a minimum of 12 h and a maximum of 48 h. Higher precision locations were collected using a Trimble GeoExplorer GPS unit to observe positions with sub-meter accuracy. For nine sites the GPS collar was positioned in extreme terrain where the Trimble unit was unusable. The actual position for these sites was estimated using Esri’s world imagery service at a ~1:4000 scale, viewing the 0.30 m resolution 2015 NAIP imagery provided by DigitalGlobe. The accuracy estimate for the image georeferencing at our sites is 6 m. The location was heads-up digitized (the process of manual georeferencing or data capture using a mouse to trace over features displayed on a computer monitor) using reference features viewable in the imagery. Distance in meters (m) of GPS collar locations to the actual location of the collar was measured using ArcGIS ver. 10 using the UTM NAD83 zone 12 projection (Esri 2011).

National Geodetic survey benchmark test

We placed the GPS collar at one National Geodetic benchmark, DM7928, near Buffalo Park in Flagstaff AZ (NGS 2015). This location has little overhead tree canopy and flat topography, ideal conditions for GPS with a clear view of the sky. The location accuracy of the benchmark is estimated to be sub-centimeter. We used the same collar and acquisition program for this test and left the collar in position from 21 June – 17 July 2012. Using Minitab 17 statistical software (2010), we explored the relationship between the location error (distance of GPS collar positions from our reference locations of actual position) and measures of DOP and fix type (2D versus 3D) recorded for the positions in the GPS collar downloaded data. We explored the relationship between location errors (distance in meters) versus DOP measures using simple linear regression ($\alpha = 0.05$) (Lewis et al. 2007). After Lewis et al. (2007) we also linearly regressed the natural logarithm (LN) transformed average location error and the average PDOP for a site. The LN transformation was used to improve normality. Location error was compared between 2D and 3D fixes using a t-test of LN transformed data.

To explore whether or not the four screening options proposed in Lewis et al. (2007) were successful in removing observations with large location errors and result in the remaining dataset used for analysis being more precise, we plotted histograms (data density) of the location error collected at the random sites. We fitted distributions for all fixes, and compared it to the distribution of fixes screened and retained using the four options. We used the exponential distribution to describe the location error distribution due to the continuous nature of the data, the data having only positive values, and the low frequency of large location error values.

To explore the accuracy of attribution of locations with GIS covariate data for spatially explicit resource selection estimation, we intersected the locations obtained at the benchmark locations with 30 m resolution GIS datasets and calculated the percentage correctly attributed. To assess how the data screening options may reduce sample size in analyses of animal deployed collars, we screened data collected from 17 Telonics GEN3 GPS collars deployed on free ranging cougars, inhabiting the same study area the stationary collar tests were performed (Supplementary material Appendix 1).

Results

We acquired 1627 GPS locations over 67 random sites, with sites having fix success rates ranging from 0.00–100.00% and an average of 89.51%. The mean location error for this range of conditions was found to be 40.81 m $\pm$ 63.89 standard deviation (SD). The ideal conditions at the benchmark location, where we acquired 312 locations, had a lower mean location error of 13.38 m ± 14.90 SD. The median location error was also twice as much for the random sites at 16.83 m compared to 8.63 m at the benchmark (Supplementary material Appendix 1 Table A1.1). The fix success rate at the benchmark location was 99.70%.

The linear regression of the LN average location error and the average PDOP of a site showed a weak positive relationship, $y = 0.94 + 0.01x$, $r^2_{adj} < 0.01\%$ (Supplementary material Appendix 1 Fig. A1.1). VDOP showed a significant negative relationship with location error, with a coefficient of –3.38 ± 0.84 standard error (SE) and p-value < 0.01. But accounted for very little of the variance with an $r^2_{adj} = 0.94\%$ (Table 1c). A t-test of LN transformed distance between 2D (n = 885) and 3D (n = 739) fixes showed a significant difference (p-value < 0.01, degrees freedom = 1601) with 2D fixes having a larger location error than 3D fixes (Supplementary material Appendix 1 Fig. A1.2). Site characteristics of terrain, canopy cover and vegetative height were relatively better indicators than DOP of location error (Table 1e–g) with all three of these covariates having p-values < 0.05 in simple linear regressions. Topographic openness explained the most variance with an $r^2_{adj} = 12.03\%$. Combining these environmental site conditions into a multivariate model explained 15.08% of the adjusted variance (Table 1h).

We screened GPS fixes using the four options provided by Lewis et al. (2007) using the random site test dataset. We plotted the data density of location error for all fixes, those screened, and those retained for the four data screening options and fitted each group with an exponential distribution (Fig. 1). Option one (i.e. screen fixes with a PDOP greater than ten) resulted in a four percent data reduction and the location error of the screened data having a mean location error of almost twice the mean of the retained data. The screening however, did not alter the data density nor the mean location error between all the fixes and the

Table 1. Linear regression results of location error (m) as a function of PDOP (a), HDOP (b), VDOP (c), TDOP (d), topographic openness (e), vegetation height (f), canopy cover (g), and a multivariate model of environmental conditions (h) at the 64 random field sites located in northern Arizona, USA, during 2011–2012. Some covariates, VDOP, terrain, vegetation height and canopy cover, were found to change with changes in location error (T-test of significant slope p-values < 0.05). These relationships were not found to be strong however, with large regression standard error (S) values (± 59–64 m from the regression line) and low r^2_{adj} values showing little of the variance was explained by the regressions.

	Coefficient	SE	T value	p-value
(a) Position dilution of precision – PDOP				
Intercept	40.85	1.59	25.70	< 0.01
PDOP	–0.00	0.02	–0.37	0.71
$S = 63.90$ $r^2 = 0.01\%$ $r^2_{adj} = 0.00\%$				
(b) Horizontal dilution of precision – HDOP				
Intercept	40.84	1.59	25.70	< 0.01
HDOP	–0.01	0.02	–0.32	0.75
$S = 63.90$ $r^2 = 0.01\%$ $r^2_{adj} = 0.00\%$				
(c) Vertical dilution of precision – VDOP				
Intercept	47.74	2.33	20.52	< 0.01
VDOP	–3.38	0.84	–4.05	< 0.01
$S = 63.59$ $r^2 = 1.00\%$ $r^2_{adj} = 0.94\%$				
(d) Time dilution of precision – TDOP				
Intercept	40.87	1.59	25.69	< 0.01
TDOP	–0.02	0.04	–0.44	0.66
$S = 63.90$ $r^2 = 0.01\%$ $r^2_{adj} = 0.00\%$				
(e) Terrain – topographic openness				
Intercept	435.20	26.50	16.45	< 0.01
Openness	–4.66	0.31	–14.93	< 0.01
$S = 59.92$ $r^2 = 12.08\%$ $r^2_{adj} = 12.03\%$				
(f) Vegetation – height (m)				
Intercept	30.77	4.50	6.80	< 0.01
Height	0.70	0.29	32.37	0.02
$S = 63.80$ $r^2 = 0.35\%$ $r^2_{adj} = 0.28\%$				
(g) Vegetation – canopy cover (%)				
Intercept	32.37	2.90	11.03	< 0.01
Canopy	0.19	0.06	3.41	< 0.01
$S = 63.68$ $r^2 = 0.71\%$ $r^2_{adj} = 0.65\%$				
(h) Environment – multivariate model				
Intercept	526.00	173.00	3.04	< 0.01
Openness	–5.85	1.97	–2.98	< 0.01
Height	–7.80	1.97	–2.98	0.44
Canopy	1.92	0.47	4.09	< 0.01
Openness × Height	0.09	0.11	0.79	0.43
Canopy × Height	–0.10	0.03	–3.60	< 0.01
$S = 58.87$ $r^2 = 15.35\%$ $r^2_{adj} = 15.08\%$				

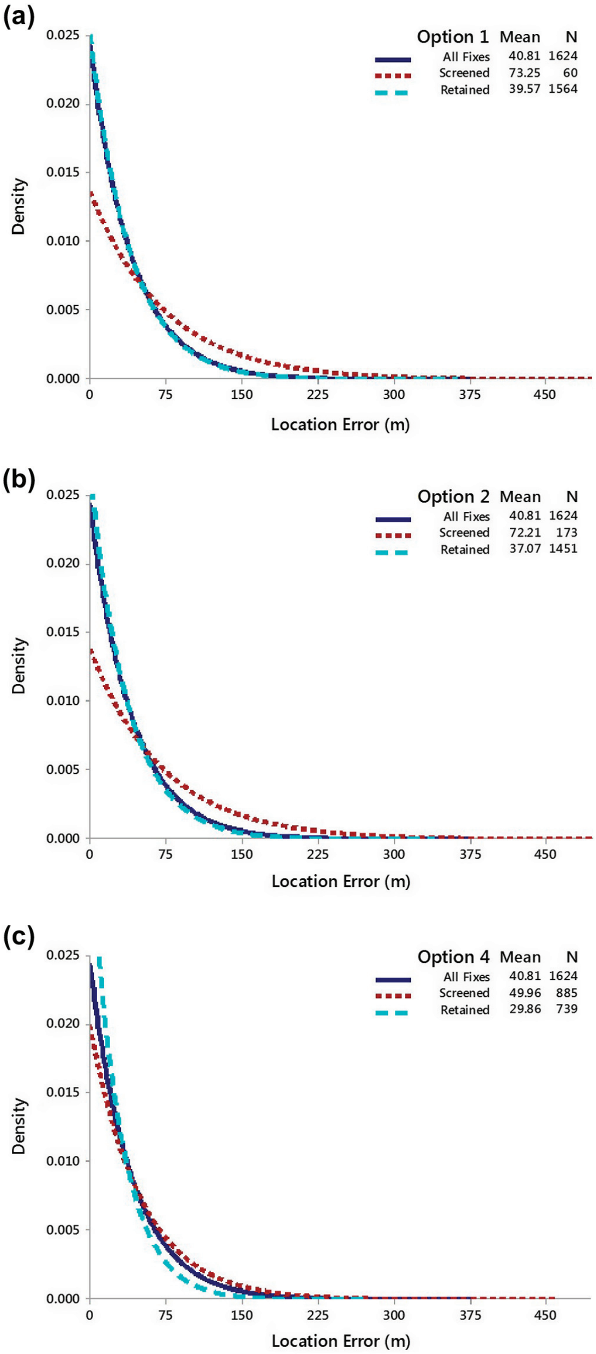

Figure 1. Location error histograms fitted with exponential distributions from random site tests displayed with all data and with the four data screening options from Lewis et al. (2007). Option one (a), excluding all locations with a PDOP greater than ten, resulted in a 3.69% data reduction. Option two (b), excluding all 2D positions with a PDOP greater than five, resulted in a 10.65% data reduction. Option three, excluding 3D positions with a PDOP greater than ten and 2D positions with a PDOP greater than five, had the same result as option two because we did not obtain any 2D positions with a PDOP greater than five. Option four (c), screening all 2D positions, resulting in a 54.50% data reduction. For all four options the screened fixes had a relatively higher location error, but for options one through three, the data screening neither had a large influence on the mean location error nor changed the distribution of location error for all the data and the retained data. Option four did reduce the mean location error by 10.95 m but also reduced the number of fixes by more than half.

retained data (Fig. 1a). Options two and three had the same result, since we did not acquire any fixes that were 3D and had a PDOP greater than ten. These options (i.e. screen 2D fixes with a PDOP greater than five) resulted in an 10.65% data reduction, and a similar result to option one, where the screened fixes had a mean location error of almost twice the mean of the retained data, but screening did not substantially alter the mean or the distribution of the location error for the retained dataset (Fig. 1a). Option four (i.e. screen all 2D fixes) resulted in a 54.50% data reduction and reduced the mean location error from 41 m to 30 m, reducing outliers, and shifting the distribution towards smaller location errors. The data screening options had similar data reduction rates on the cougar deployed collar datasets, with option one resulting in 1.06–4.55%, options two and three resulting in 6.87–11.23%, and option four resulting in 36.92–58.28% data reduction (Supplementary material Appendix 1 Table A1.2).

For the benchmark test, two DOP measure were found to be a significant covariate, PDOP and HDOP; PDOP with a coefficient of 0.86 ± 0.51 SE and p-value equal to 0.01 and HDOP with a coefficient of 1.48 ± 0.62 SE and p-value equal to 0.02. But PDOP only explained 0.57% of the adjusted variance and HDOP only explained 1.49% (Table 2). A t-test comparing the LN transformed location error between 2D GPS fixes ($n = 49$) and 3D GPS fixes ($n = 263$) showed no significant difference (p-value $= 0.78$, degrees freedom $= 65$). We found no evidence of bias in location error towards any direction with the angle of the direction of the GPS position to the benchmark being roughly uniformly distributed (Fig. 2). The intersection of the 30 m resolution raster covariate, topographic openness (Ironside and Peters 2015) and the GPS collar locations, resulted in 70% of the locations intersecting the correct grid cell despite a slight offset of the benchmark in relation to the cell center (Fig. 2a). Because of the continuous nature of the topographic openness measure and how features on the landscape are distributed, most of the positions fell into a cell of similar value to the true location (Fig. 2a). For a categorical variable with high spatial variability at the benchmark site, LANDFIRE's existing vegetation height (US Geological Survey 2011), 77% of the locations intersected the correct category (Fig. 2b). Displaying the location of GPS fix PDOP (Fig. 2a) and fix dimension (Fig. 2c) does not show a pattern of outlier fixes as having high PDOP values or being 2D fixes.

Discussion

Our tests of a GEN3 Telonics GPS collar over a wide range of conditions known to affect the performance of GPS technology, showed vegetation and terrain can influence position accuracy in addition to fix success rates (Ironside et al. 2015). Comparing location error at an ideal site with little obstruction of the sky-view to location error from randomly stratified locations covering a range of sky-view obstruction, showed under ideal conditions location error was 13.38 m, but across the range of conditions in our study area, the accuracy is 40.81 m on average. The ability to relate site conditions to location error was not consistent though,

Table 2. Linear regression results of location error (m) as a function of PDOP (a), HDOP (b), VDOP (c) and TDOP (d) for positions acquired in the summer of 2012 at the National Geodetic Survey benchmark site, DM7928, located near Buffalo Park, Flagstaff, Arizona, USA. PDOP and HDOP showed a significant change with changes in location error (T-test of significant slope, p-values < 0.05). These relationships were not found to be strong however, with a low r^2_{adj} value showing little of the variance was explained by the regression. The standard error (S) of the regressions was $\pm$ 15 m from the regression line for all four regressions.

	Coefficient	SE	T value	p-value
(a) Position dilution of precision – PDOP				
Intercept	9.77	2.32	4.20	<0.01
PDOP	0.86	0.51	1.67	0.01
$S = 14.86$ $r^2 = 0.89\%$ $r^2_{adj} = 0.57\%$				
(b) Horizontal dilution of precision – HDOP				
Intercept	10.03	1.63	6.14	<0.01
HDOP	1.48	0.62	2.39	0.02
$S = 14.79$ $r^2 = 1.81\%$ $r^2_{adj} = 1.49\%$				
(c) Vertical dilution of precision – VDOP				
Intercept	12.42	1.88	6.59	<0.01
VDOP	0.29	0.51	0.57	0.57
$S = 14.92$ $r^2 = 0.00\%$ $r^2_{adj} = 0.00\%$				
(d) Time dilution of precision – TDOP				
Intercept	11.38	1.97	5.76	<0.01
TDOP	0.82	0.73	1.12	0.26
$S = 14.90$ $r^2 = 0.40\%$ $r^2_{adj} = 0.08\%$				

and our multivariate model using GIS derived metrics of topographic openness and vegetation canopy density and height to measure obstruction to the sky-view, was only able to explain 15% of the variance. We found reported dimension and DOP measures for fixes to be poor predictors of location error, and only Option four, screening all 2D fixes (Lewis et al. 2007), reduced location error in the remaining dataset. Option four also reduced the number of observation in our dataset by nearly half, and also screened relatively high proportions of fixes with small location errors (Fig. 1c).

Unlike previous studies (Moen et al. 1996, Dussault et al. 1999, D'Eon and Delparte 2005, Lewis et al. 2007) PDOP was not as strongly related to location error. Though using a PDOP cut-off greater than five screened fixes with a mean location error of almost twice the remaining data, a large proportion of the retained fixes have low location error (Fig. 1). Our results suggest neither dimension nor the DOP measures provide information on fixes with large location errors under ideal sky-view conditions. Under these ideal conditions though, the odds of a fix being attributed with the correct GIS covariate are high at a 30 m resolution for both continuous gradients and highly variable categorical covariates. Therefore data screening idoes not yield many benefits in this particular situation. Under conditions with some obstruction to sky-view vertical DOP and 2D fixes provide weak information in regards to location error. Removing 2D positions to increase accuracy can have pronounced data reductions, which could result in biasing datasets towards shorter vegetation types, lower canopy cover, and/or more exposed terrain. This also reduces a large percentage of fixes with little location error (Fig. 1) and could have pronounced influence on measures of animal movement from consecutive fixes in time.

Here we covered a wider range of conditions than Lewis et al. (2007) that resulted in high rates of failed fix attempts for a portion of our sampling sites. Where sky-views are obstructed from topography and vegetation, satellite signals can be reflected and diffracted (multipath) and/or weakened (attenuation from passing through obstructions), distorting the signal. This could possibly also distort and affect the ability to produce PDOP measures that reflect the actual location error when fix attempts do not fail. Previous studies (D'Eon et al. 2002, Lewis at al. 2007) addressing screening for location error using DOP used Lotek Wireless Inc. (Newmarket, ON, Canada) and Advanced Telemetry System (ATS, Isanti, MN) collars. It is also possible that differences in GPS hardware and software between these brands and the Telonics collar used here, resulted in the difference in findings. Pseudorange estimation, especially parameterizing the effects of the ionosphere and troposphere in signal delay, are an active area of research and differences in the models used for these correction factors between brands could also contribute to the difference in findings. Although Frair et al.'s (2010) review paper suggests that Telonics collars provide the highest accuracy fixes compared to other GPS wildlife collars, our findings remain limited to this individual collar until additional units can be tested. In future testing of collar accuracy, we recommend independent measures of the location of collar test sites. Our assessment in Supplementary material Appendix 2 of the location error of GPS collar centroids, suggests under certain conditions, centroids can have a location error up to 89.12 m.

Since our results suggest location error is difficult to screen in our study, special attention needs to be given to mean location error and how habitat characteristics are mapped in terms of resolution, accuracy, and variability (Frair et al. 2010, Montgomery et al. 2011). The ability to correctly attribute observations in GIS, is a function of the mean location error and characteristics of model covariates in terms of the spatial grain of mapping and 'patch size'. Fig. 2b illustrates the effect of patchiness and location error where areas with high variability in classification and small patch size can lead to the increased likelihood that an observation is incorrectly attributed (Montgomery et al. 2011). Likewise imagine the benchmark had been located 90 m to the west, in an area classified as a contiguous large patch of forest height 10–25 m. The percentage of correctly attributed observations would go up significantly. On the other-hand moving

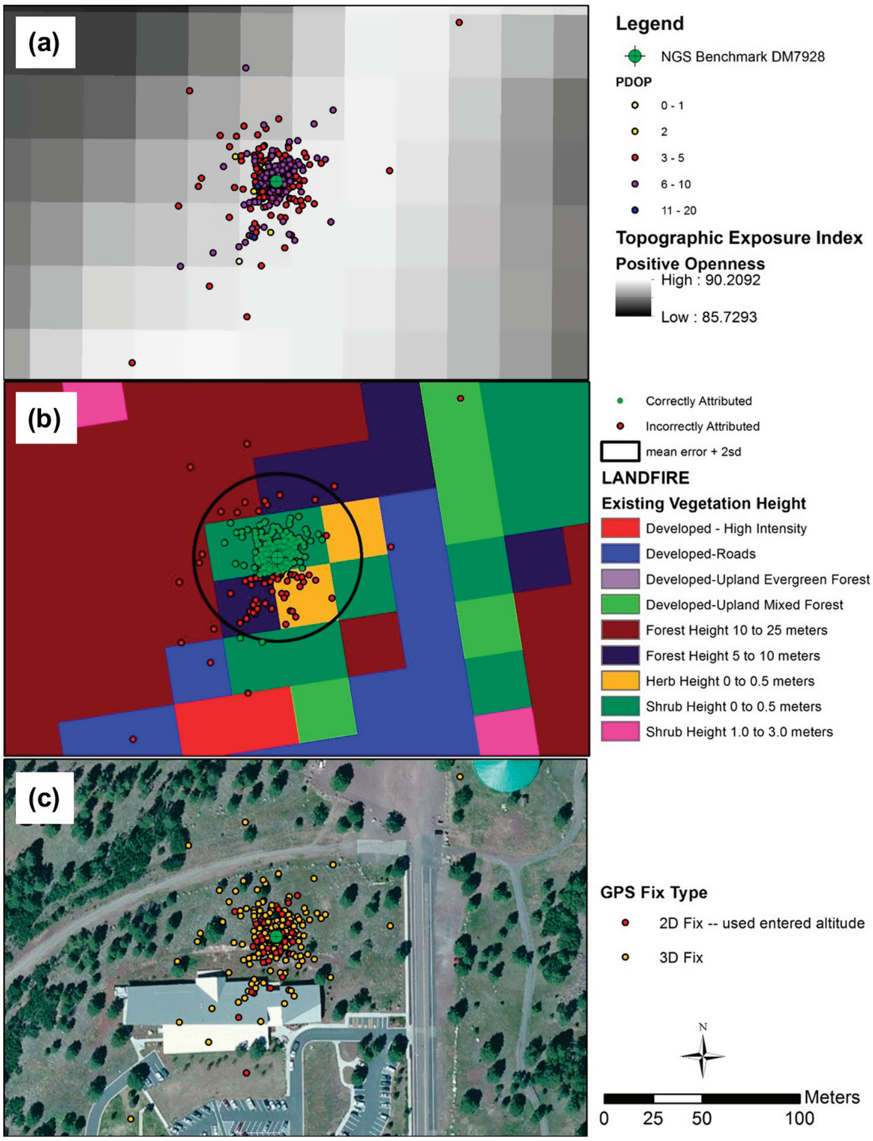

Figure 2. Location of GPS collar fixes and true location of the Telonics GEN3 collar at NGS benchmark DM7928; displayed with GPS fix PDOP value overlaid on topographic openness (a), shown with GPS fixes in relation to LANDFIRE's existing vegetation height classes (b), and shown as GPS fix type, 2D or 3D, overlaid with aerial imagery (c).

the true location 90 m to the west in Fig. 2a would decrease the likelihood that an observation would be attributed with a similar value of topographic openness. Therefore our confidence that an observation is correctly attributed is affected by minimum mapping unit, edge effects, and the configuration of the landscape. The accuracy of GIS mapping is yet another consideration when evaluating how confident we are at inferring how animals respond to characteristics of the landscape (Johnson and Gillingham 2008).

Our results did suggest mean location error could be reduced from 41 m to 30 m across our study area using option four but would also result in large data loss in our deployed collar datasets. For example, cougar C2 in Supplementary material Appendix 1 Table A1.2, had a fix success rate of 53.16%, and option four resulted in screening 48% of the successful fix attempts, leaving a quarter of the fix attempts for analysis. Depending on analytical techniques employed and the distribution of the data, the reduction in sample size could make the analysis more sensitive to outliers (Van Selst and Jolicoeur 1994) and nullify the effect of screening. Larger sample sizes tend to result in more robust models (Nams 1989). The large reduction in observations could also result in underestimating total movement in analyses employing metrics such as step-length and turn angle (Mills et al. 2006) and miss short duration movements associated with particular activities. Alternative screening methods have been proposed based on properties of animal movement (Bjørneraas et al. 2010) but their utility is dependent on sampling interval, the mobility of study animals, and distances of location error.

Conclusions

Studies utilizing observations of animal locations acquired via GPS tagging are numerous and technological advances are making GPS tagging of more species applicable every day. Advancements in technology are also resulting in higher precision of GPS positioning and other GIS mapping products. In terrestrial applications of GPS technology, it is well known that vegetation and terrain interfere with satellite signals. Efforts to explicitly consider GPS error in studies of habitat use are becoming more prevalent and the utility of location error screening is often treated as transferable across study areas and collar specifications. PDOP has been a popular method for screening location errors, but we demonstrate here that it has few benefits for our study area and collar. Our study suggests more attention needs to be given to study specific environmental conditions and technology for screening of location error. Understanding the mean location error across conditions present in the study area and the utility of dimension and DOP measures for identifying observations with large location error, affects the appropriate scale of covariates and study questions that can be addressed.

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Supplementary material (available online as Appendix wlb-00229 at <www.wildlifebiology.org/appendix/wlb-00229>). Appendix 1–2.