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Using footprints to identify and sex giant pandas

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ABSTRACT

Data on numbers and distribution of free-ranging giant panda are essential to the formulation of effective conservation strategies. There is still no ideal method to identify individuals and sex this species. The traditional bite-size method using bamboo fragments in their feces lacks accuracy. The modern DNA-based estimation is expensive and demands fresh samples. The lack of identifiable individual features on panda pelage and no apparent sexual dimorphism impede reliable estimation from camera trap images. Here, we propose an innovative and non-invasive technique to identify and sex this species using a footprint identification technique (FIT). It is based on a pairwise comparison of trails (unbroken series of footprints) using discriminant analysis, with a Ward's clustering method. We collected footprints from 30 captive animals to train our algorithm and used another 11 animals for model validation. The accuracy for individual identification was > 90% for individuals with more than six footprints and 89% with fewer footprints per trail. The accuracy for sex discrimination was about 84% using a single footprint and 91% using trails. This cost-effective method provides a promising future for monitoring wild panda populations and understanding their dynamics and especially useful for monitoring reintroduced animals after the detachment of GPS collars. The data collection protocol is straightforward and accessible to citizen scientists and conservation professionals alike.

1. Introduction

The giant panda (*Ailuropoda melanoleuca*) is one of the world's most iconic threatened species, with an estimated 1864 pandas surviving in the wild (State Forestry Administration, 2015). Although protected areas cover 54% of the suitable habitat (State Forestry Administration, 2015), this species still faces serious threats such as habitat loss and fragmentation (Loucks et al., 2001; Li and Pimm, 2016). The giant panda now lives in six mountain ranges and is isolated into 33 subpopulations. Of these, 22 have fewer than 30 individuals, and 18 have fewer than ten individuals and some of them are on the brink of extinction (State Forestry Administration, 2015). For their long-term survival and management, understanding giant panda population dynamics is crucial. To date, there are no ideal methods for individual and sex discrimination. Direct observation and counts are impossible because of low population densities, complex topography, and elusiveness of the species (Zhan et al., 2006). Unlike tigers or leopards, the similar appearance of individual pandas, with no identifiable features such as stripes or spots, makes them difficult to differentiate from camera trap images. Here, we suggest a practical field method to sex and identify individual pandas.

Currently, there are two primary methods to identify individual giant pandas: the bite-size technique and DNA-based approaches. The bite-size technique was originally used to differentiate age groups of pandas (Schaller, 1985) and then was extended to identify individuals (Garshelis et al., 2008). Studies of giant pandas in the wild and captivity have shown individual differences in "bite size" and "chew rates" of the bamboo stems in their droppings (Schaller, 1985; Yin et al., 2005). The bite size is usually derived from measuring 100 stem/leaf fragments in droppings (Yin et al., 2005). This method has been used for the third (1999–2003) and fourth (2011–2014) national survey of giant pandas (State Forestry Administration, 2015), but it lacks scientific rigor (Wei et al., 2002; Zhan et al., 2006). It is less reliable in denser population areas or within mating clusters because many individuals may have similar bite sizes. Moreover, some significant variation in bite sizes within individuals could result in overestimating numbers (Zhan et al., 2006). Finally, this method requires field staff to make very precise measurements to apply the threshold of 2 mm (Yin et al., 2005). Human and measurement tool errors are often unable to meet this level of precision (Zhan et al., 2006).

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The alternative is using microsatellite analysis with fecal DNA (Zhan et al., 2006). This non-invasive DNA sampling was also used in the fourth national giant panda survey (State Forestry Administration, 2015). Believed to be more accurate than the traditional bite-size estimate (Wei et al., 2015), its accuracy requires the sample to be very fresh to exclude potential degradation and contamination of DNA. The extensive survey effort required and challenges in finding sufficient samples have prevented applying this method successfully in large-scale studies. The cost of processing samples in the laboratory has impeded the use of DNA individual identification for most conservation practitioners.

There is no apparent sexual dimorphism in the giant panda. Because the external sexual organs are small and cryptic, it is difficult to identify the sex of giant pandas in the field, or even in captivity, without a DNA test. Adult males are 10–20% larger than adult females (Smith et al., 2010). There is much variation, however, and it is particularly difficult to identify the sex of a solitary, free-ranging animal, outside the breeding season. This problem is exacerbated when it comes to identifying the sex of sub-adults (Yang et al., 1999).

Reintroduction has been a crucial part of panda conservation, especially to revive the small and isolated local populations. GPS collars are only used for these reintroduced pandas and are set to drop off after two years. Reintroduction needs to be evaluated in the long term and requires novel non-invasive methods to monitor these individuals.

These challenges have motivated the development of a robust and cost-effective technique to balance the accuracy required of a population estimate with the need for a low-cost field tool. The Footprint Identification Technique (FIT) has become a promising and cost-effective tool in wildlife conservation in recent years (Pimm et al., 2015). This non-invasive technique was first developed for black rhinos (Jewell et al., 2001). More recently it has been successfully adapted and applied for cheetah (Jewell et al., 2016), white rhinos (Alibhai et al., 2008), Amur tiger (Gu et al., 2014), mountain lions (Alibhai et al., 2017; Jewell et al., 2014) and other endangered species.

Footprints have been used as signs of giant panda presence for many years (Fan et al., 2011; Wang et al., 2014; Li et al., 2015). Their footprints are characteristic of the species, and if the substrate permits, easily found.

We report the development of the giant panda FIT for individual and sex identification, a potentially powerful tool to assist with the management and conservation of this endangered species. FIT can play an important role in monitoring the demographics of giant panda populations. China now has around 375 captive giant pandas and an active re-introduction programme is underway (State Forestry Administration, 2015). Since FIT requires the initial establishment of a training database with known individuals to extract the necessary algorithms, the captive-bred population proved to be an ideal resource. The development of this technique for the giant panda could help establish an individual database of footprints for the free-ranging populations.

2. Methods

2.1. Study population

We collected footprint images from 41 captive giant pandas in the China Conservation and Research Centre for the Giant Panda (CCRCGP) in Sichuan, China. It has three major captive bases; Ya'an, Du Jiang Yan, and Wolong. The Wolong base is located in the heart of Wolong National Nature Reserve, which is one of 67 reserves designated by China's government to protect wild giant pandas (State Forestry Administration, 2015). Several enclosures are built in the forest, each with an average area of 0.33 km^2. This natural habitat provides conditions for rehabilitating animals which are to be reintroduced to the wild.

2.2. Study period

We collected images from captive animals from March 2014 to April 2016, mostly on a prepared sand substrate since snowfall was infrequent at the lower altitudes where captive pandas are held. Fresh sand was used for each animal to avoid any possible disturbance of behaviors from olfactory cues. At the same time, we collected footprints on snow from captive animals at Wolong when enough snow had accumulated in the higher-altitude enclosures.

2.3. Foot anatomy and data collection

In addition to the five digits, the giant panda has an unusual feature on the front feet – a 'sixth finger' or 'sesamoid pad'. This structure acts as an opposable digit and is an adapted and enlarged radial sesamoid bone from the wrist. This exaptation enables giant pandas to grab bamboos more efficiently and to facilitate feeding (Endo et al., 1999). Thus, a clear front footprint usually shows six distinct digit pads along with the metacarpal and carpal pads. The sesamoid bone imprints are unique to giant panda prints. For our purposes, they have the advantage of adding complexity to the footprint, thus enabling the extraction of a more effective FIT algorithm from the morphometrics (Fig. 1).

Initial trials to investigate the clarity of the prints left by each of the four feet also indicated that front foot impressions were more distinctive, detailed, and clearly outlined. This was likely due to a combination of greater weight at the front of the animal and less fur on the front feet. We arbitrarily chose the left front foot for the FIT model development. In common with bear species, pandas tend to over-step or side-step. That is, instead of registering the hind foot impression on that made by the front foot, the hind foot usually falls in front of the front foot print or to one side, leaving a clear front foot impression.

We define a *trail* to be an unbroken series of footprints from one animal. We took images of each left front footprint from directly above with a carpenter's scale in the trail according to the protocol described in Jewell et al. (2016). The form of each footprint may vary with the gait of the animal, substrate type, moisture levels, slope of the ground and weather conditions. To account for this variation within the footprint metrics of each individual, we collected multiple footprint images from each panda.

2.4. Extracting a geometric profile

In total, we collected 521 usable footprints along 76 trails from 41 individuals (see Supplementary Table 1 for individual information).

We imported each digital footprint image into a customized FIT addin in JMP software from SAS, resized and rotated for standardization (Jewell et al., 2016). Scale points 1 and 2 were placed on the ruler at an interval of 10 cm. Landmark points were then placed manually at anatomical positions on the footprint, following software prompts. In other species, the edges of the pads are more clearly defined e.g., the cheetah (Jewell et al., 2016). In the giant panda, the edges of the pads are less clearly defined due to different substrates on where footprints can be found in the field, so we used the centroids for landmark points 1 to 6 on the toe pads and sesamoid pad, and the distal end of pad for landmark point 7 (Fig. 2). Using these landmark points, JMP automatically computed a further 15 derived points and then 124 metrics consisting of lengths, angles and areas (see Supplementary Table 2 for details). The collection of these metrics allows all measurements that one anticipates might prove useful in discriminating between footprints.

3. Data analysis

3.1. Individual identification

The FIT customized model for classifying trails employs pairwise

Fig. 1. Foot anatomy and footprints of the giant panda. Left front foot on the left and left hind foot on the right with their prints below. A) digital pad; B) metacarpal pad; C) sesamoid pad; D) carpal pad. The corresponding pads, a, b, c and d are shown in the footprint image.

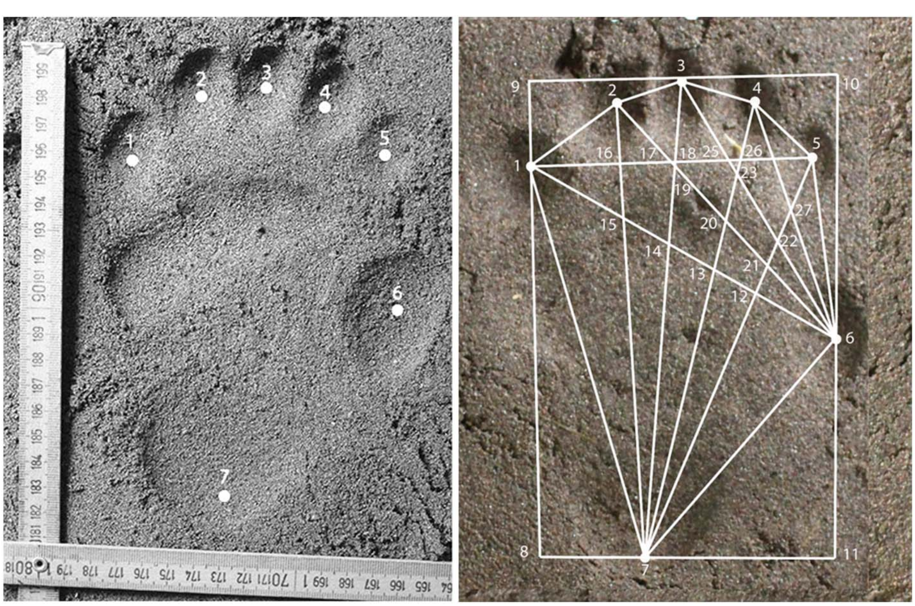

Fig. 2. Landmark points and computed derived measurements. On the left, the 7 landmarks that are input manually, 1–5 on centroids of the digital pads, 6 on centroid of the Sesamoid pad and 7 on the distal end of the carpal pad indentation. Points 1 and 5 were used as rotation points along a horizontal axis. On the right, the 7 landmarks with the derived measurements and other variables that FIT generates automatically.

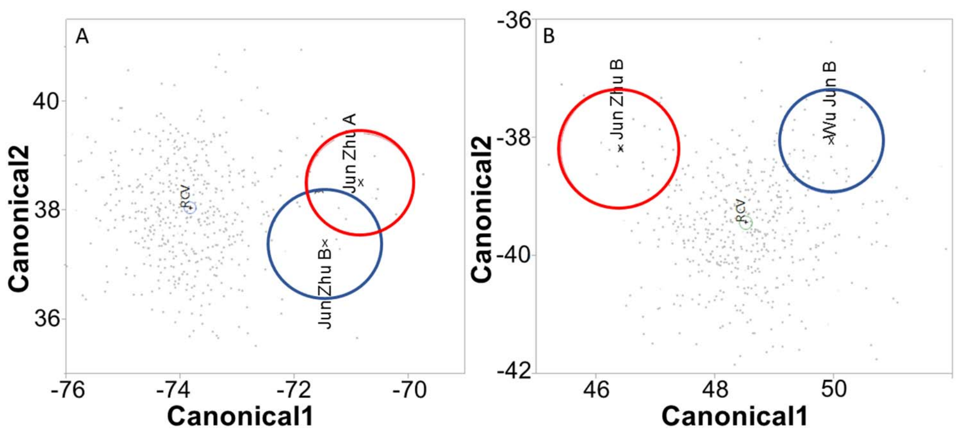

Fig. 3. Two way canonical plots showing positions of centroid values and 95% confidence interval ellipses for trail data from same individual (A) and two different individuals (B) in FIT analysis. The analysis is performed in the presence of a constant, the Reference Centroid Value (RCV). Each single point represents a footprint. In A, the blue and red ellipses for trail data are from the same individual Junzhu, a female, and in B, two different individuals (blue for the male Wu Jun and red for Jun Zhu). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Details of 30 individuals each with a minimum of six footprint images per trail used in the training set.

	# of individuals	Mean age (range)	# of footprint images	Mean # of footprints (range)	# of trails	Mean trails/ individual (range)
Females	16	9.6 (2–15)	273	17.1 (8–31)	38	2.4 (1–4)
Males	14	7.5 (2–14)	204	14.6 (6–33)	29	1.1 (1–4)
Total	30	8.6 (2–15)	477	15.9 (6–33)	67	2.2 (1–4)

comparison of trails using discriminant analysis (Jewell et al., 2016). During this process, each pair combination of trails is held back as the test set with the rest of the trails utilized as the training set model building. The top explanatory measurements are selected using forward stepwise regression according to their *F*-ratio. Then the first two canonical variates are constructed to map the trails in this two-dimensional space. The centroid values (multivariate least-square means) and 95% confidence interval ellipses are plotted for each trail. In the FIT model, the presence/absence of overlap of the ellipses is used as a classifier. If the ellipses overlap, then these two trails are likely to belong to the same individual (Fig. 3).

The distance between the centroids is relative, depending on the matrix of within-group variations and the relative-position vector of the centroids. Thus, any changes of a testing set (adding or removing individuals) would alter the positions of the centroid values as well the ellipses. To solve this problem, we applied two modifications proposed by Jewell et al. (2001). First, we applied the centroid plot technique on a pairwise basis, comparing two trails at a time. Second, we constructed a “Reference Centroid Value (RCV)” using the other known individuals in the library as a reference point in the canonical space. The RCV functioned to stabilize the location of any test groups with respect to each other (Alibhai et al., 2008; Jewell et al., 2016; Alibhai et al., 2017).

When testing the accuracy of a species FIT algorithm it is necessary to optimize the values of three features within the FIT model construct: the number of variables in the model, the size of the confidence intervals around the ellipse, and the threshold value of the distances between the means. The supplementary materials discuss the process of identifying the optimal combination of these three parameters.

To test the robustness of our model, we ran sequential holdback trials with random portioning of the dataset into test and training sets. By varying the number of individuals in the training set, we tested the accuracy of the model in predicting the number of individuals in the test set. We used this process to get an overview of the most effective combination of the three parameters (see supplementary materials). Then we ran a more detailed sequential holdback trial. We started with a test/training set ratio of 3/27 randomly selected individuals with the optimal combination of the three parameters and increased the test size at intervals of 3. For each test/training set ratio, we iterated the process ten times and plotted the predicted means for each set against the actual test set size.

The final output in FIT is in the form of a cluster dendrogram giving a predicted number of individuals (Jewell et al., 2016; Alibhai et al., 2017). It identifies the Ward distance between each pair of trails, which is the distance between two clusters in the dendrogram. This distance is computed from the ANOVA sum of squares between the two clusters summed over all the variables. It is the basis for identifying whether each pair of trails are from the same individual or two different individuals. Individuals predicted to be the same by the algorithm were clustered together and given the same color-code.

We analyzed the data in three stages. First, of the 41 individuals, 30 had trail(s) with a minimum of 6 footprints per trail. Footprint images for these individuals were from a sand substrate and we used these to extract the algorithm in FIT for individual identification. Table 1 summarises the sex ratio, age, numbers of footprints and trails pertaining to the 30 individuals. Then we conducted the within model validation.

We divided our independent test dataset into two sets. The first test set had two individuals from the enclosure with natural habitat. The second test set had nine individuals with fewer than six footprints and was used to test a limited sample size.

3.1.1. Sex discrimination and age-class distribution

We analyzed the data using discriminant analysis to generate a predictive model to discriminate sex in the giant panda. We performed linear discriminant analysis (LDA) sequentially using an increasing set of measurements selected stepwise to identify the asymptote for the accuracy. The stepwise measurement selection was used to generate a parsimonious set of measurements, based on F-ratios, which provides the most power to discriminate sex (Gu et al., 2014). It also excludes highly correlated variables that may bias the estimate. Five-fold cross-validation was used to evaluate the model. Since there was a possible interaction between sex and age in the giant panda with regard to foot morphology, we divided the individuals into five age classes (A: 0–2.9 yrs old, B: 3–5.9 yrs old, C: 6–8.9 yrs old, D: 9–11.9 yrs old and E: > 12 yrs old, see Table 3 in Supplementary for details) and subjected sex/age classes to discriminant analysis.

4. Results

4.1. Individual identification

4.1.1. Systematic holdback trial

The optimal combination of three parameters for the model is 12

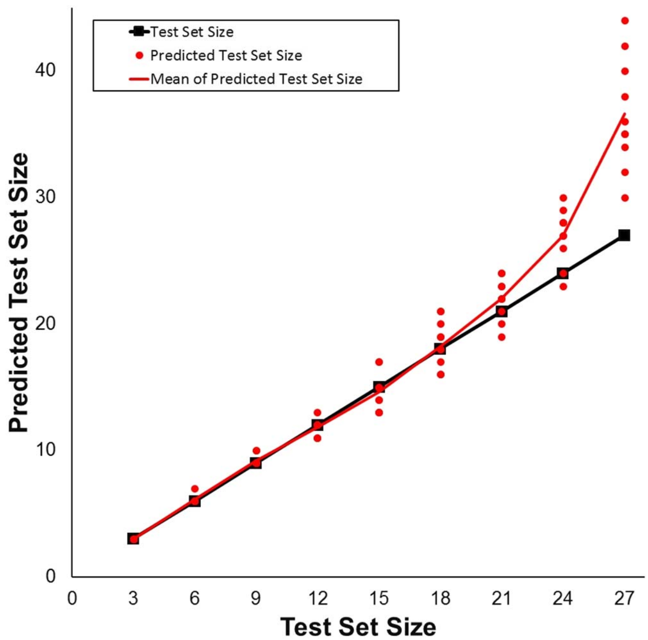

Fig. 4. The result of a comprehensive holdback trial for 30 pandas. If the test set size equals 3, then the training set size is 27 to build the model. The process was iterated 10 times for each test set size. The solid black line represents the 1:1 line of the true values (black squares). The red dots are the ten predicted values at each test set size. The red line represents the means of predicted test set size. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

variables, 95% confidence interval and 1.5 as the threshold value. The FIT provided a more accurate estimate when the training set was > 12 individuals (Fig. 4). With larger training set sizes, the predicted test set size matched the actual test set size very accurately and the range around the mean remained small. At a ratio of 15 training/15 test and 12 training/18 test, the range around the mean increased and beyond that, the level of accuracy of prediction declined.

4.1.2. Model validation

Using the above algorithm for the giant panda, we tested its efficacy in three stages. First, we ran the FIT analysis for the data set of 30 individuals with 477 footprints and 67 trails. Fig. 5A shows that the FIT model predicted 28 individuals (93.3% accuracy) with seven of the 67 trails misclassified (89.6% accuracy). The distance threshold determines the numbers of clusters and hence the predicted number of animals. Varying the threshold, the relative estimated likelihood of accuracy for 27 individuals was reduced to 78% (Fig. 5B). The distribution of “chance” is calculated as the relative probability of predicting a specific number of individuals compared to the auto output number. However, the likelihood for 29 or 30 individuals remained high at 91% (Fig. 5C) and dropping off thereafter to 72% for 31 individuals. In other words, the FIT predicted 28–30 individuals.

Second, we iterated the analysis with a total of 32 individuals including two trails collected from semi-enclosures in a snow substrate from two known individuals. Fig. 6 shows that the model predicted 29 individuals (90.6% accuracy) with the two added trails from Yeye and Zhangka being identified correctly as separate individuals.

Third, we ran the accuracy assessment with the additional trails from the nine individuals that had fewer footprints than the requisite minimum number (6) for the FIT model. We analyzed these nine trails using the same algorithm in the FIT model. The model predicted eight individuals giving a surprisingly high accuracy (88.9%) (detail dendrogram in the supplementary).

4.2. Sex discrimination

Since age of individuals could affect the analysis, we compared the mean ages of females (n = 20, $\bar{x}$ = 10.18, SE = 1.03) and males (n = 20, $\bar{x}$ = 7.5, SE = 1.03) (the age for one female was not known). There was no significant difference (F Ratio = 3.35, $p > 0.05$). Fig. 7 shows the number of variables versus accuracy of sex prediction for the dataset using linear discriminant analysis. The asymptote was reached at an accuracy of about 84% using single footprints with approximately 30 measurements. The accuracy level even with as few as five variables was above 75%. To assess the accuracy using trails, we used a simple majority of misclassified footprints in the trails as a classifier. Of the 79 trails, seven were misclassified and one was an even split, giving an accuracy of 91.0%.

4.2.1. Sex and age-class interaction

We subjected the data to LDA using different sets of variables selected stepwise and it became clear that while the other age classes for the sexes showed a clear difference in a two-way canonical plot, the youngest age classes for males and females appeared to be very similar. This suggests that female and male pandas under the age of three years appear to have very similar foot shape and size. Fig. 8 shows a two-way plot using the first two canonicals generated by LDA with 20 variables selected stepwise (age classes FA and MA were excluded for this analysis). There appeared to be a marked difference in the distribution pattern for the sexes.

5. Discussion

The literature now recognizes the importance of developing robust, reliable and cost-effective non-invasive techniques for censusing and monitoring populations of endangered species (Jewell et al., 2016; Pimm et al., 2015; Alibhai et al., 2017). Invasive methods requiring capture, handling and tagging of animals can have negative effects ranging from subtle changes such as alteration of sex ratios (Moorhouse and MacDonald, 2005) to dramatic reductions in fertility (Alibhai et al., 2001).

The Footprint Identification Technique (FIT) is non-invasive. We show that metrics derived from footprint images of the giant panda successfully identify individuals, determine sex and, to some extent, classify them according to age. In particular, the sequential holdback trial gave predictions for estimated numbers of individuals in the samples very similar to the actual numbers. This analysis with 30 individuals (Fig. 6) indicated that even with a training set of 12 individuals, the predicted mean of the ten iterated values for the 18 individuals in the test set was very close to the actual test set size. However, the high variation around the mean suggests that a training set of around 12 individuals for building the model would lead to inconsistencies in prediction accuracies. For the giant panda, we would suggest a training set of 20 individuals with an even sex ratio as a minimum number for individual identification using FIT.

Free-ranging giant panda sub-populations exist at relatively low population densities where FIT can provide the opportunity to monitor individuals or simply provide regular population estimates. This is necessary because the technique requires that the variation in shape and size of footprints due to extraneous factors such as gait, weight distribution, substrate type etc. be taken into account in the development of the model. Previously we have shown that for the FIT model, six to eight footprints per trail is the optimum number (Alibhai et al., 2008). When we tested the efficacy of the FIT model for the giant panda on trails with fewer than six footprints, the predicted accuracy (eight individuals) was still very close to the actual number (nine). The two trails from two different known individuals which were incorrectly identified as belonging to the same individual had only two and three footprints per trail. This suggests that with relatively smaller sub-populations of about ten individuals or where only a part of a population

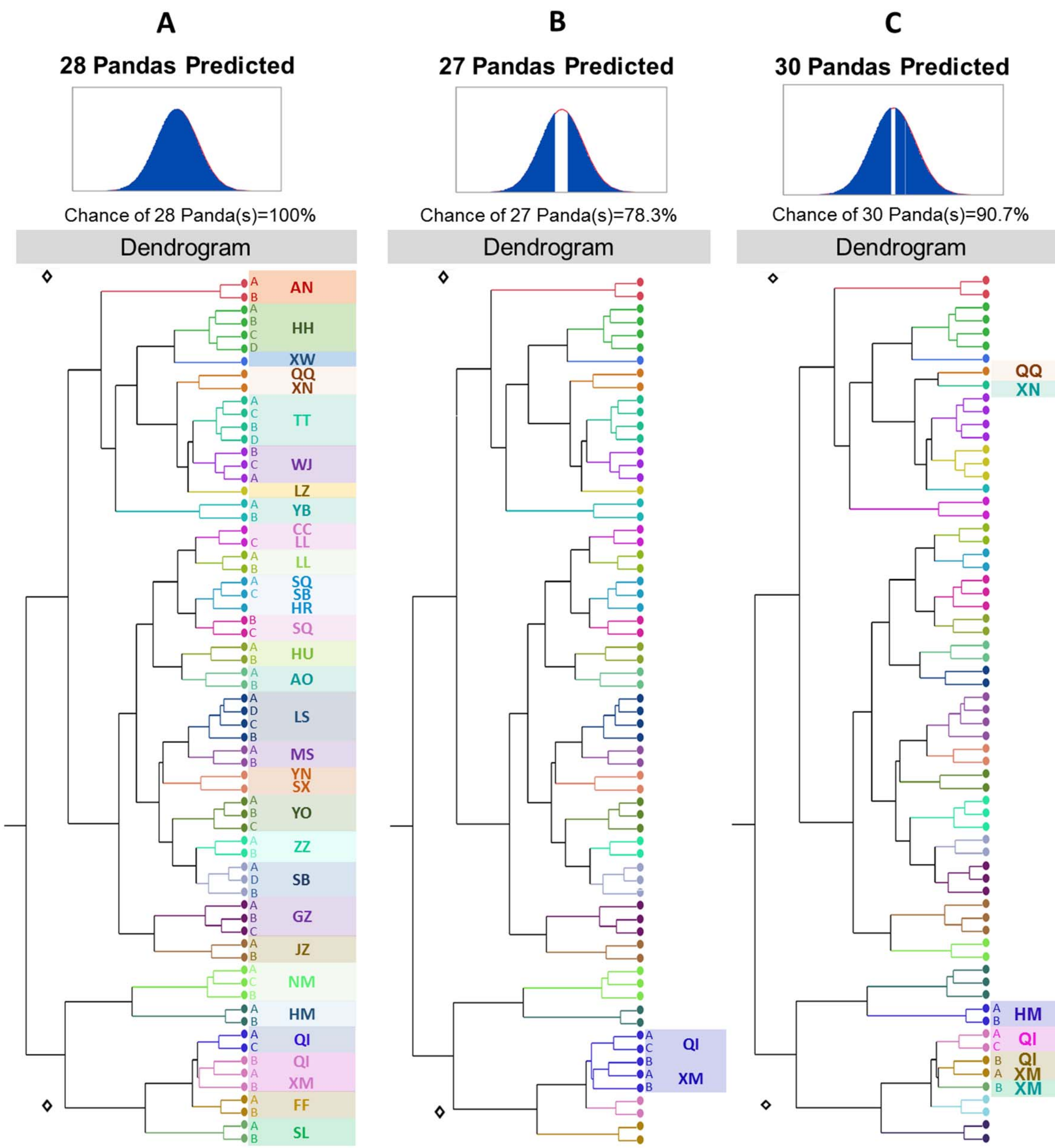

Fig. 5. Cluster dendrograms for 67 trails from 30 individuals showing classification of trails and predicted values. This is a simplified figure from the FIT output (see supplementary materials for original output figure). The FIT model predicted 28 individuals (A), with a 78.3% likelihood of 27 individuals (B) and a 90.7% likelihood of 30 individuals (C). The same shade stands for the same individual identified by FIT. The smaller fonts in the first column stand for the trail ID and the bigger fonts on the second column denote different known individuals. The diamond shows the threshold value. Any trails to the right of it are identified as the same individual. The distribution of "chance" is calculated as the relative probability of predicting a specific number of individuals compared to the auto output number (28 in this case). See Table 1 in Supplementary for the key to animal names.

is being sampled, even three to four footprints per trail would give accurate identification of individuals.

We examined the possibility of classification interaction between age and sex. Although there is very little sexual dimorphism in the giant panda, males and females show different growth patterns in their footprint morphometrics. In particular, the disparity between the sexes shown by age class changes for the measurement 'Area 8' was quite marked (see supplementary materials). Using multiple variables, once again, a two-way canonical plot, generated using discriminant analysis, showed that footprints for the sexes differed. However, our sample sizes for the age class groups were too small to draw any definitive conclusions. Since there was no significant difference between the mean ages of the sexes, linear discriminant analysis using a varying set of measurements selected stepwise, showed that even with as few as five variables, the prediction accuracy was quite high. A five-fold trial (training/test % ratio of 80/20) with five variables gave a mean accuracy for the five trials of 82%. For a repeat trial with 35 variables, the mean accuracy was 86%.

The models in this paper are already scripted into an add-in in JMP software. The software can be made available free-of-charge to conservation organizations after participation in a training workshop and by application to JMP. Basic level digital cameras or phones can be used to take photos following the standard procedure. Where routine surveys are taking place, there should be little or no extra cost to collect footprints. Thus, FIT provides a cost-effective way to identify and sex individuals, monitor their population dynamics, and to carry out research and formulate effective conservation strategies.

6. Field application

Good quality footprints are crucial. The minimum requirement for the footprint is that one can recognize its key features — five toe pads,

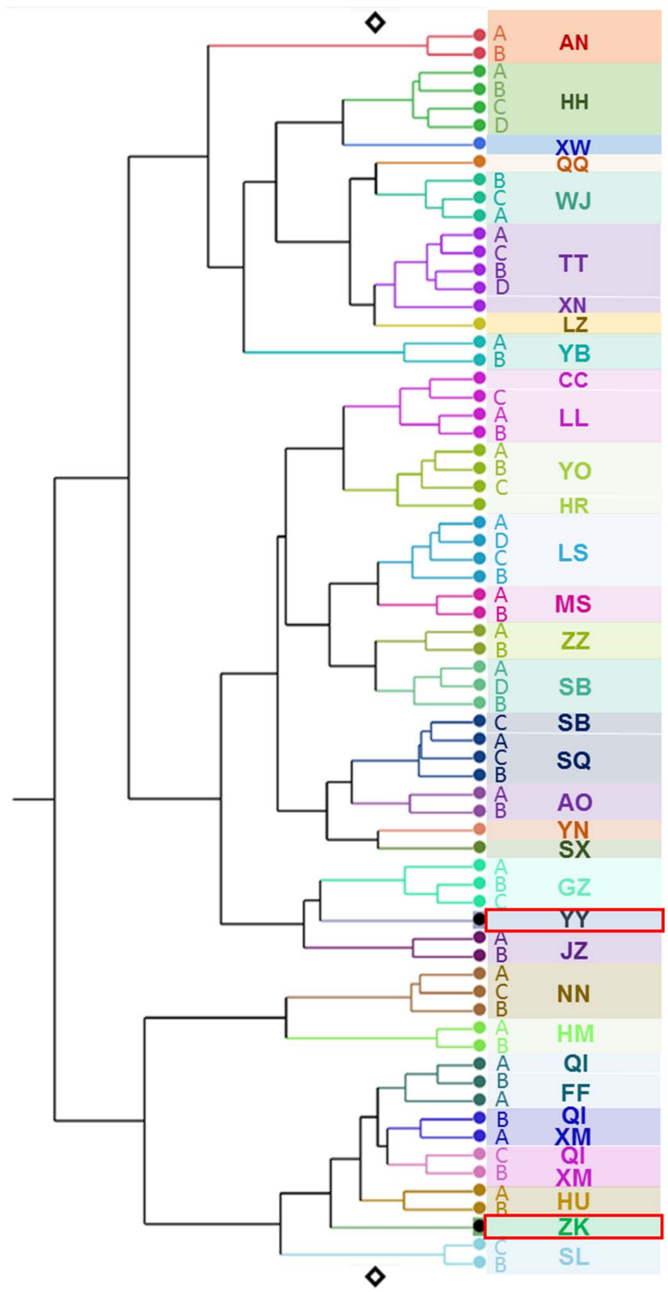

Fig. 6. Cluster dendrogram for 32 known individuals including trails collected in snow substrate from two separate individuals YY (Yeye) and ZK (Zhangka) from a semi-enclosure. A, B, C etc. denote different trails from the same individuals. The model predicted 29 individuals with the two added individuals, YY and ZK (highlighted with red boxes), identified correctly as separate individuals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

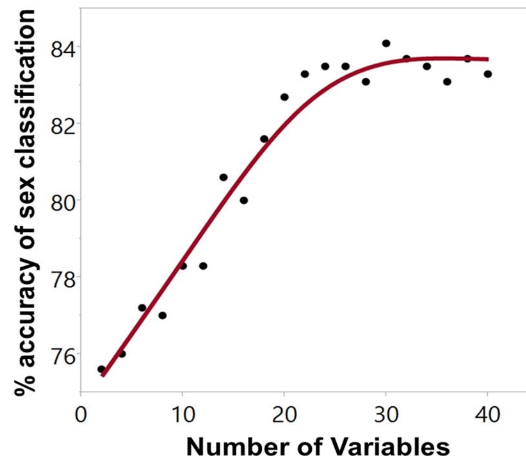

Fig. 7. Numbers of variables (measurements) and percentage accuracy of sex classification based on individual footprint metrics. The variables were selected stepwise based on *F*-ratios in linear discriminant analysis.

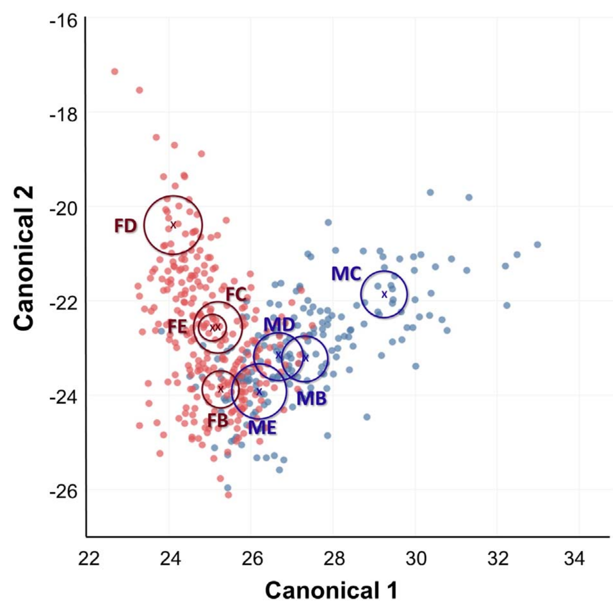

Fig. 8. Two-way canonical plot generated using discriminant analysis with 20 footprint measurements selected stepwise for different age classes of female and male pandas. The red dots were from female footprints and blue dots were from males. Age class A (0–2.9 years) for both sexes was excluded from the analysis. F for females, M for males. B, C, D, E for age classes in the main text. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Sesamoid pad and carpal pad. Although our method is robust for different substrates, it is unable to deal with distorted footprints that may happen when the animals climb up and down the steep slopes. To improve the usability of images, we recommend focusing footprint survey efforts on ridges and valleys where there is flatter terrain likely to hold complete and clear footprints. These areas are also ecologically important for pandas and frequently used as trails, water sources, and territory marking sites (Schaller, 1985; Liu et al., 2005; Hull et al., 2014). In addition, most of the ongoing field survey or monitoring programs use camera traps in this flatter terrain. Thus, using valleys and ridges takes into account both the feasibility of field surveys and usability of footprint images. It is also relatively difficult to find panda prints in areas with deep leaf litter and moss cover. We recommend carrying out footprint surveys when there is snow.

When a footprint is spotted in the field, the staff should follow the direction of the footprint and search for the whole trail. Ideally, 3–6 left front footprints should be collected from a trail. Images can be taken using a range of digital cameras and smartphones, depending on availability. A carpenter's scale or two rulers should be laid perpendicular along the bottom and left axes of the footprint, with reference to the direction of travel. A paper ID slip is laid adjacent to the scale and included it in each image that records GPS location, date of collection and ID of the footprint. Great care should be taken to capture images from directly above the footprint and perpendicular to the plane of the footprint to avoid parallax error. Then the photos can be imported to the FIT software for analysis.

Like any conservation monitoring technique, FIT has advantages and limitations. The collection of fresh and clear footprints requires a commitment to fieldwork, especially in snowy conditions. Locating footprints efficiently comes with experience, and the help of local trackers is often invaluable. Field staff needs training in how to identify panda footprints and the correct foot for FIT. We encourage researchers to investigate innovative ways to combine this technique with traditional methods such as camera trapping and facilitate the deployment of FIT for panda monitoring year-round,

China is committed to the reintroduction of captive-born giant pandas to the wild to diversify the genetic pool and keep the population stable. Since 2010, seven pandas have been reintroduced, and five have survived. The GPS collars on these animals drop off automatically after two years, so it is difficult to track these animals afterwards. FIT could serve as a long-term and low-cost tool to monitor these individuals after the first two years. It could provide insights into the range changes, activity levels, interaction with other individuals and many other crucial aspects regarding the success of reintroduction in the long term.

This cost-effective and non-invasive technique also empowers local conservation practitioners, and particularly those with tracking skills or other traditional ecological knowledge, to monitor Pandas and evaluate conservation projects on their own. Moreover, this technique can be used for citizen science. As tourism increases to southwest China, visitors can be engaged to collect footprint images as per FIT protocol and contribute to giant panda conservation.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2017.11.029.

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