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EFFECTS OF WEATHER ON DETECTION OF LANDMINES BY GIANT AFRICAN POUCHED RATS

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Although APOPO has trained mine detection rats for many years, no published data exist on how weather parameters relate to detection accuracy. Using data taken during routine training, we show that there was little relationship between the detection success of rats and rainfall but find that rates decreased, on average, with increasing temperatures and increased with higher humidities. Individual rats vary in terms of sensitivity to temperature in that

1. a small number of rats appear to work better at higher temperatures, and
2. most rats showed relatively low sensitivity to temperature at normal training temperatures. However,
3. there was a proportion of rats for which temperature sensitivity may be affecting detection reliability, and identifying these rats relatively early in training should aid decision making about operational deployment.

Dogs and other animals function as odor-detection tools for an increasing array of detection applications outside the laboratory. Examples include the scat of endangered species, humans in collapsed buildings, cadavers, accelerants at fire scenes, contaminated land, weeds, landmines, and there are many more.[1–8] It is broadly assumed that biological odor detectors working outdoors will be affected by environmental variables such as temperature, humidity, and wind.[7–10] However, as also noted by Reed et al., we found surprisingly little empirical exploration of odor-detection success for animal detectors in relation to varying environmental conditions.[11]

Little or no effect of local weather conditions was found for dogs locating scats of mustelids or bears in a temperate forest environment in the Eastern United States.[12] However, detection success improved with increasing number of days since precipitation, and increasing relative humidity for dogs searching for carnivore scat.[11] For dogs searching for tortoises in a desert environment, significant effects on detection success were found for temperature (higher temperatures = better success), humidity (lower relative humidity = better success), and wind speed (increasing wind speed = better success).[13] In a study in a cool temperate forest environment, detection success improved with increasing temperatures, but humidity had no effect.[14] The temperature and humidity ranges experienced in these last two studies were quite different, being relatively hot and dry in Long et al. study, while relatively cool and moist in Sargisson et al's study, possibly explaining some of the differences.[13,14]

Limited research is available regarding the effect of weather variables on the success of landmine- or explosives-detection dogs, who typically work outdoors and often under extreme environmental conditions. Sargisson et al. explored the effect of temperature, humidity, and rainfall on landmine detection by dogs in Afghanistan during trials spanning a full operational season for the dogs.[8] All data were gathered during normal operational conditions. No effect was found for temperature on detection success (i.e., hit rate), and some evidence was found for a negative relationship between humidity and hit rate. As humidity declined under the dry conditions experienced in Afghanistan, hit rates increased, and a strong effect was found for rainfall. Afghanistan had experienced four years of drought prior to the study, and most of the dogs were not likely to have experienced rain or have ever worked over moist ground. Significant rain fell early in the study, hampering detection success by increasing the number of false alarms and reducing the hit rate due to runoff spreading mine odor across the minefield.

The scant research on how weather parameters impact the odor-detection success of dogs shows mixed results, possibly because success is linked to normal operational and training experiences. If the weather moves outside those parameters as it did during the Afghanistan study, the dogs may struggle.[8] For rats, we have found no published research investigating the effects of weather variables on odor-detection, probably because most work with rats is undertaken in laboratory conditions. We know of only one program in which rats serve as field-based odor-detectors: the use of giant African pouched rats (Cricetomys gambianus) by *Anti-Persoonsmijnen Ontmijnende Product Ontwikkeling* (APOPO).[15] These rats are trained for landmine detection in Morogoro, Tanzania, which lies at 6 degrees 49 min south latitude and 37 degrees 40 min east longitude, and is situated at elevation 504 m above sea level. They are currently working operationally on the Mozambique-Zimbabwe border, and in Angola and Cambodia, all areas with warm, temperate to tropical climates.[16,17] Thus, the

Figure 1. Rats undergoing training in the APOPO landmine-training field in Morogoro, Tanzania. The handlers (in blue) have a line attached to one leg, spanning the width of the box. The rat is wearing a harness that is attached to the line, allowing it to move back and forth along the line. The supervisor is in white.
Photo courtesy of APOPO.

rats are operational in weather conditions that are similar to, but somewhat more variable than, the conditions under which they were trained.

In this study, we undertook a retrospective analysis of data collected by APOPO in its training minefields to explore the effects of temperature, humidity, and rainfall on detection success of giant African pouched rats searching for landmines in Morogoro, Tanzania.

METHODS

APOPO supplied a file of information on the performance of rats during training and testing up until August 2016 in a minefield containing about 800 boxes. A box is a marked area of land between 60 and 400 sq m, contains zero to seven buried mines, and is surrounded by safe lanes. The search of one box represents one row of data. The file contained the details of each box: date, search time, rat identification, number of mines present (0–7), number of mines found, number of false alarms, and various administrative details. We calculated the proportion of mines found (p = number mines found / number present, range 0–1), average search time of the box (time of start and end were both listed), and logit p as per Equation 1.

Eq.1 $$\text{Logit } p = \log_{10}\left(\frac{p+0.01}{(1-p)+0.01}\right)$$

No weather variables were recorded by APOPO, and we obtained these separately as described below.

We rejected boxes for which there were obvious data-entry errors (such as time inconsistencies, missing data, or where $p > 1$), all boxes searched outside the standard training period of 06:30 to 09:30, very short or very long searches (< 10 min, > 45 min), and all searches where boxes contained no mines. The edited data set consisted of 6,798 boxes for 217 rats and was further reduced to 4,723 boxes after rejection of any box described as a blind test (there were relatively few of these per rat), any rat that searched fewer than 10 boxes all together, and all data before 2015. Larger sample sizes per rat were available in 2015 and 2016 than were available for earlier years. For a small number of boxes, some data were removed as there were a few days for which we could not obtain reliable weather data.

The final data set contained information on searches of more than 10 boxes during training for each of the 86 different rats for the period 5 January 2015 to 10 August 2016; the average number of boxes per rat was 35.6, with a 95% confidence interval (CI) [30.82, 40.38]. Some rats were still in training, while others had completed training and were either deployed operationally or otherwise lost from the program. Following the criteria above, we included all rats for which data were available; we did not reject rats that died or failed accreditation.

TRAINING PROGRAM

When searching at the outdoor training field, a rat works on a line between two handlers who operate a running lead to keep the rat moving in the correct direction (Figure 1). The average time for a rat to complete a standard 100 sq m box is 19 min, 44 sec (n = 4,779) for training. If a supervisor is present, he or she will record indications as reported by the handlers. If no supervisor is present, no data are recorded. The availability of a supervisor to record data appeared to be entirely independent of the factors we were studying, and we do not regard the missing data as relevant to this study.

Rats receive initial training at the APOPO laboratory. Once they are deployed to the field, they go through three training stages:

1. **3 m boxes** are 60 sq m, contain a high density of mines (4–7), and have a 3 m axis on one side;
2. **5 m boxes** are of varying sizes up to 100 sq m, contain a medium density of mines (3–7), and have a 5 m axis on one side; and
3. **advanced boxes** are also of various sizes with dimensions up to 400 sq m, these contain a low density of mines (1–4).

Boxes containing no mines can be used at any stage of training. The number of boxes searched at each stage of training in the final data set was quite variable across rats, often including no boxes for one stage, and we ignored stage of training in this analysis. Searches involving boxes with zero mines were rejected, because we were analyzing for the effects of weather variables on proportion of mines found.

In training, handlers know where all mines are in the box and reward most correct indications (i.e., found mines) by the rats. As

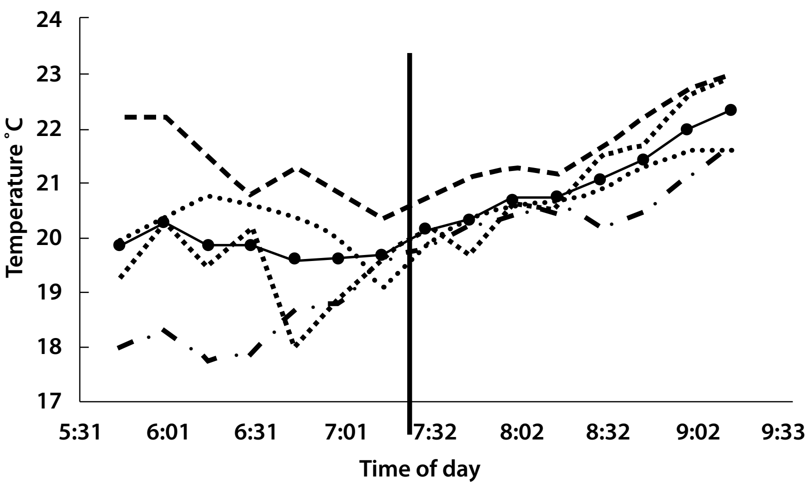

Figure 2. Temperature change through the morning from 05:45 to 09:15 on four days in the third week of August, 2016. The average values used in modelling are shown as a solid line. The vertical line is the time when the sun hits the ground.
All figures courtesy of the authors.

handlers are not blind to the location of the mines, they can aid the rat in finding a mine by adjusting the criteria to accept a hit, or by gently manipulating the running line. However, there were still a large number of missed mines in the data set, and we hypothesized that a proportion of those misses were linked to variation in weather variables.

WEATHER DATA

Obtained from a government-run weather station 1 km from the training site, weather data were available for every day in the 2015–2016 period; however, the reported details were inconsistent. Temperature and relative humidity were usually reported at 06:00 and 09:00, and sometimes also reported for 07:00, 08:00, and 10:00. Rainfall was reliably reported as a total for the whole day, but information on specific times of rainfall was rarely reported. Wind speed and direction were rarely reported and were ignored. Rats work close to the ground and were not worked in windy weather, thus they are unlikely to be affected by wind. Nor were they worked if the grass was wet or the ground boggy due to their tendency to stop constantly to groom.

Needing more precise weather information than was available from the station, we built models using the available data in order to predict temperature and humidity at the precise times that rats searched the boxes. For rainfall, we estimated rain (in mm) in the 24 hrs before each training day using Equation 2.

Eq. 2 (mm of rain on day before the search) + (1/2 mm of rain on day of search)

Equation 2 was adjusted if any information on when rainfall occurred in the day was available, e.g., if all rain that fell on the day of the search fell after the time of the search, then none of that rain was included for the day of the search. When such information was not available, we used half the rainfall as an estimate of what may have already fallen at the time of the search in the morning. Rats did not undergo training if rain fell during the usual training period but were trained if overnight rain had been light or was threatening and had not yet fallen.

In order to build the weather models, we recorded temperature and humidity every 15 min from 05:45 to 09:30 on 17 (temperature only), 19, 20, and 21 August 2016. It rained early on 17 August 2016, and was dry overnight with initial clear skies (at 07:00), while the other three days experienced increased cloud cover. We used the patterns recorded on those days to predict the pattern of temperature and humidity change on all other days of the year for which training data were available, using the available weather records at 06:00 and 09:00 on each day to anchor the models and adjust them for seasonality. The model then predicted the temperature and humidity at the precise (average) time that the rat was searching a box on that day. As most boxes were searched in less than 30 min, the average time of the search approximates to the timing of an indication within 15 min or less.

The general pattern for temperature recorded in August (Figure 2) was a decline from 06:00 to a low point (between 06:30 and 07:15), followed by a steady increase to 09:15. For humidity, the pattern was an increase to a peak (between 07:00 and 07:45) followed by a steady decline to 09:15 (Figure 3, page 46). There was some variation in scale and timing of the low or high point on the days that the detailed patterns were recorded, which we minimized by using values averaged across the three to four days of detailed data (solid line in Figures 2 and 3). The sun hit the ground at 07:20–07:25, which is consistent with the switch to increasing temperature and declining humidity in the data.

Due to the low latitude and the variability in this small data set, we did not attempt to adjust the models for the time of sunrise at other times of the year. Rather, we depended on the data from the weather station at 06:00 and 09:00 to anchor the models, and accepted that the estimates of temperature and humidity used in the analyses here are subject to error that is controlled for, but not eliminated, in the models.

Being tropical, weather variation at Morogoro is influenced as much by rainfall and humidity as by temperature. There are two wet seasons: November and April (the April wet season is longer and with more rain), and winter temperatures are only a few degrees cooler than summer temperatures. Across a full year, the minimum and maximum temperatures measured at the Morogoro station were 14 and 28 C respectively for 06:00 and 09:00, with a typical range of 3–4 C on any day. Thus, in August,

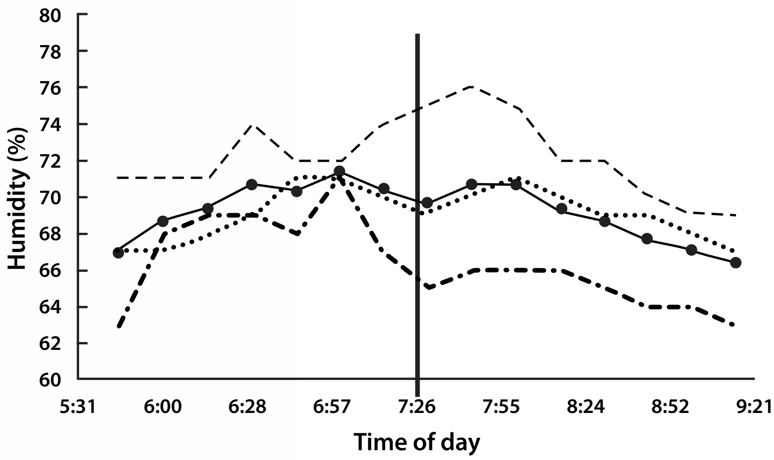

Figure 3. Humidity change through the morning from 05:45 to 09:15 on three days in the third week of August, 2016. The average line used in modelling is shown as a solid line. The vertical line is when the sun hit the ground.

a typical temperature range was 17–20 C, and in January, it was 22–25 C. We are confident that the models predicted temperatures with reasonable accuracy, especially after 07:00 when most of the boxes were searched.

Humidity was considerably more variable than temperature on a day-to-day basis (Figure 3). Model predictions were therefore likely to be of lower accuracy than for temperature. However, these predictions still give the best available estimate of humidity at the time of the search.

ANALYSES

We analyzed the data in two ways. First, we determined the effects of each of the three independent weather variables (temperature, humidity, and rainfall) on the dependent variable (proportion of mines found; here converted to logit p, see Equation 1, page 44) using linear mixed modelling. Second, a descriptive analysis was essential to understand the patterns in the data, and we give examples of those analyses here to provide background for the study. All analyses used each rat as the subject that delivers the dependent variable. Thus, the reported sample size for any analysis was the number of rats, with any variation in sample size of rats (n), caused by missing weather data resulting in the rat being excluded from a particular analysis.

The number of search boxes available for each rat ranged from 10 to 80. That large range created difficulties for statistical analyses exploring variation across rats in a repeated-measures design. We therefore collapsed the data for each rat in two ways.

First, for each rat we collapsed p (Logit p) data into categories by calculating mean values for weather variable units: for temperature, data were collapsed into 1 C units (range <15–27+ C, giving 14 categories); for humidity, data were collapsed into 2.5% units (range <67.5–100%, giving 14 categories); for rainfall, data were collapsed into unit ranges of increasing size with increasing rainfall (details in **Results**), giving 10 categories. The maximum n of 14 or 10 unit categories was usually less for each rat, as no data were available for some unit ranges for most rats, even if the original sample size was large (as described previously, the uncollapsed n was 10–80). Analyses were then performed on those partially collapsed measures.

The proportion of mines found (p) is bound by the values 0 (none found) and 1 (all found), and is therefore not appropriate for parametric statistical analyses, which require unbounded dependent variables. Therefore p was converted to logit p as per Equation 1. The conversion creates an unbounded value for p, where a p of 0.5 = 0, a p of 1 = 2 or more, and a p of 0 = -2 or less. The adjustment of 0.01 avoids incalculable logit p values when p = 1 or 0.

Second, for descriptive purposes, we calculated Pearson's correlation coefficients (r) across all boxes for each rat between each of the three weather variables (temperature, humidity, and rainfall) and proportion of mines found. Pearson's r approximates the slope of the regression line for the rat in relation to the weather variable, and serves as a proxy measure enabling comparison across rats using a single value. A large number of correlation coefficients were calculated, and our purpose was descriptive, thus we do not report significance. Pearson's r ranges from -1 to +1. If r is positive, p increased as temperature, humidity, or rainfall increased. If r is negative, p declined as those variables increased. If r is close to zero, p can be considered to be unaffected by the weather variable. As r becomes larger, i.e., approaches +1, detection success by the rat is increasingly likely to be influenced by the weather variable. However, interpretations based on the scale or significance of that influence should be cautious and supported by further analysis.

RESULTS

Individual rats potentially contributed an accuracy score at each of 14 different temperature or humidity units and 10 different rainfall units, introducing a repeated measure into the analysis.[18] Additionally, as not every rat contributed an accuracy score for every weather unit, there was incomplete data. Therefore, we ran three separate linear mixed models, one for temperature, one for humidity, and one for rainfall, using rat name as a random effect variable and the relevant weather variable as a fixed effect. For simplicity, all models were run using a homogeneous covariance structure with compound symmetry.

The model for temperature was significant, $F(1, 13) = 4.78$, $p < 0.001$, showing a significant relationship between temperature and logit p. Figure 4 (page 47), which displays the estimated marginal means for logit p at each of the 14 temperature units, shows

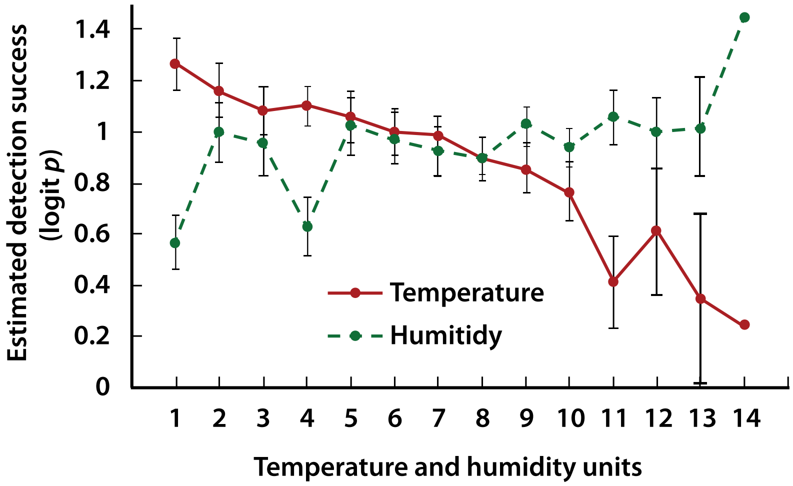

Figure 4. Estimated marginal means for logit p based on increasing values of temperature and humidity (in units). Error bars show the standard error of the mean.

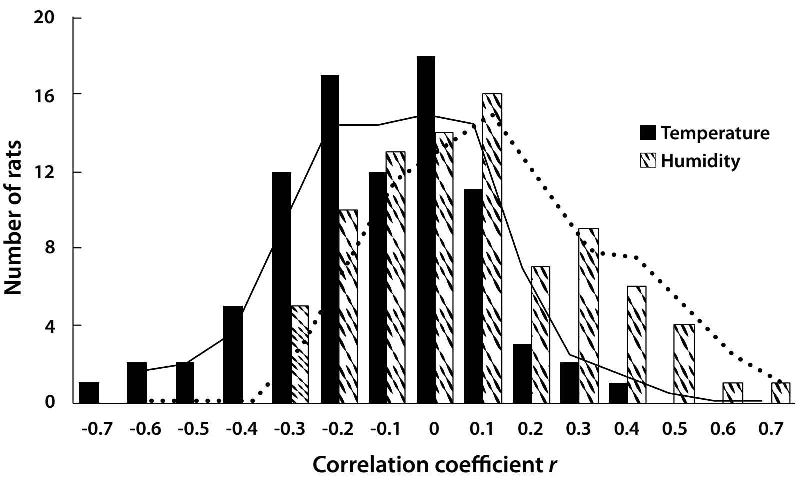

Figure 5. Distribution of Pearson's r for the relationship between temperature (solid bars), humidity (dashed bars) and p during field training to find landmines for 86 rats. Value on x axis gives the middle of the count range; e.g., the count for "0" is for the range >-0.05 to +0.05.

that logit p decreased with increasing temperature. The model for humidity was also significant, $F(1, 13) = 3.807$, $p < 0.001$, showing a significant relationship between humidity and detection success. Figure 4 shows that although detection success generally increased with increasing humidity, the pattern was slightly more variable than for temperature. The model for the relationship between rainfall and detection success was not significant, $F(1, 13) = 0.63$, $p = 0.76$, and the estimated marginal means showed no consistent relationship with logit p, and therefore these means are not shown in Figure 4.

The correlation coefficients for each rat were linked to temperature, humidity, and rainfall at the time of the search. Weather variables influence each other and are only partially independent. During the weather modelling, we noted that temperature and humidity were inversely related, whereas any relationship of either of these variables with rainfall was not readily discernible (in part because there were many days with no rainfall). Our analyses consistently indicated that temperature was most strongly related to rat detection success, humidity was less strongly related, and there was no detectable relationship between detection and rainfall. We therefore emphasized temperature and included the descriptive results for humidity, but not for rainfall.

For temperature, the ratio of negative to positive r values was 61:25 (total $n = 86$) and the average r was -0.12, 95% CI [-0.08, -0.16] (Figure 5). Thus, for most rats, detection success declined with increasing temperature, and there was a negative relationship with temperature for the average rat. The relationship between temperature and performance should be minor for rats with r values close to 0, and for 55 of the 86 rats (64%) r was within the range -0.2 to +0.2. Of the 31 rats with a stronger negative r than -0.2, seven had a very strong value (below -0.4) indicating a relatively high negative sensitivity to temperature. Four rats had a positive r over +0.2, suggesting that their detection success improved with increasing temperature. Of these, one was only trained at lower temperatures (below 20 C) and the positive r should be discounted for this animal. However, two were trained within the typical range of temperatures (17–25 C), and one was only trained at relatively high temperatures (21–27 C). Thus, while the main effect of temperature on detection accuracy is negative, there appears to be a small proportion of rats for which performance improves at higher temperatures.

For humidity, the ratio of negative to positive r values was 35:51 (total $n = 86$), and the average r was 0.07, 95% CI [0.02, 0.12]. Thus, the detection performance of rats tended to improve as humidity increased (Figures 4 and 5), with some rats showing a strong relationship between humidity and detection success (eight rats had an $r > 0.4$).

There were four rats with strong sensitivity to both temperature ($r < -0.4$) and humidity ($r > +0.4$). Of these four, one showed a steady improvement on training trials with no evidence of struggling in summer; one showed a steady overall training improvement, but its performance declined in summer; one struggled in late summer, after which its performance improved as the weather cooled, and one did not have enough data to interpret. We give these examples primarily to demonstrate how the sensitivity of individual rats can be explored if appropriate data are available.

For rainfall, the ratio of negative to positive r values was 41:44 (total $n = 85$) and the average r was -0.01, 95% CI [-0.05, +0.05].

The relationship between rainfall and detection overall was small, with only a few animals performing more or less accurately in wet conditions. However, the rainfall analysis was dominated by dry days, with about two-thirds of the searches undertaken after zero rainfall in the last one and a half days, and most others experiencing relatively little rainfall. There were only a few days in the year when substantial rain fell, and the rats were not usually trained on those days (although they might be trained the next day when a heavy rainfall would be included in the data). Overall, the number of searches on which significant rain fell was only a small proportion of the overall data set, and our ability to detect any relationship between detection and rain was therefore limited.

DISCUSSION

Overall, these results give confidence in the ability of most rats to cope with weather variation under the conditions experienced at the training fields. However, the greatest relationship between detection success and weather was found for temperature, which is frequently an issue in the places where animals (including rats) are used to search for landmines. Temperatures at ground level in environments in which there is little vegetation can rise more quickly than air temperature measured by a weather station would suggest.[8] APOPO is aware of this issue, and the trainers reported to us that lethargy could appear quickly if rats were working over bare ground, even if air temperatures were within the normal working range. Ground vegetation buffers the heating effect of direct sun, giving a longer operational time, and cloud cover is more likely when humidity is high. It appears that the most appropriate locations for these rats to work outdoors are those where humidity remains relatively high, and there is ground vegetation. We cannot comment from these data on whether there are minimum temperature limits for operational use of rats.

A small proportion of rats showed a strong enough relationship with temperature and/or humidity and detection performance to suggest that APOPO could benefit from monitoring performance in relation to weather parameters. Perhaps most importantly, it should be possible to identify those individuals for whom performance is strongly positively related to temperature and deploy them preferentially to operational theatres where temperature is likely to be an issue. Individuals whose performance is strongly negatively related to temperatures might be deployed to laboratory-based detection tasks, such as tuberculosis testing, where temperature and humidity are controlled.

A concern for APOPO is that apparently well-trained rats may still fail accreditation testing, which is a single event undertaken following the U.N.-approved mine action standards. Failure on that test could delay opportunities for operational deployment, and has resulted in individual rats being held back in their training programs. While the standards must be adhered to, the results from this study suggest that temperature may be a factor in some of those failures, and consideration of the relationship between performance of individual rats in relation to weather parameters for both testing and the proposed deployment theatre might be appropriate.

See endnotes page 65

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