Mortality estimation from carcass searches using the R-package carcass — a tutorial

Authors: Fränzi Korner-Nievergelt, Oliver Behr, Robert Brinkmann, Matthew A. Etterson, Manuela M. P. Huso, et. al.
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Mortality estimation from carcass searches using the R-package carcass – a tutorial

Fränzi Korner-Nievergelt, Oliver Behr, Robert Brinkmann, Matthew A. Etterson, Manuela M. P. Huso, Dan Dalthorp, Pius Korner-Nievergelt, Tobias Roth and Ivo Niermann

This article is a tutorial for the R-package carcass. It starts with a short overview of common methods used to estimate mortality based on carcass searches. Then, it guides step by step through a simple example. First, the proportion of animals that fall into the search area is estimated. Second, carcass persistence time is estimated based on experimental data. Third, searcher efficiency is estimated. Fourth, these three estimated parameters are combined to obtain the probability that an animal killed is found by an observer. Finally, this probability is used together with the observed number of carcasses found to obtain an estimate for the total number of killed animals together with a credible interval.

What is carcass used for?

Collisions of bats and birds with man-made structures such as large buildings, towers, wind turbines or traffic are of ecological concern (Schaub and Lebreton 2004, Kunz et al. 2007). To assess mortality rates, systematic searches for carcasses are often performed. The number of carcasses found, however, largely underestimates mortality because only a subset of the animals killed fall into an area that is searched (the ‘search area’). Furthermore, many carcasses may be removed by scavengers before the searches. Finally, of the dead animals that have not been removed by scavengers some may remain undetected because the probability of finding a carcass during a search usually is less than one. In order to obtain unbiased estimates of mortality from systematic carcass searches the following three parameters must be measured or estimated: 1) proportion of animals killed that fall into the search area \( a \), 2) carcass persistence probability \( s \), and 3) searcher efficiency \( f \). The proportion of animals killed that fall into the search area \( a \) can be obtained from the spatial distribution of the search area in relation to the spatial distribution of the carcasses. The spatial distribution of the carcasses mainly depends on the type of obstacle they collide with. The package carcass includes a table with empirical and theoretical distributions of bat carcasses beneath wind turbines of different sizes. However, the spatial distribution of the carcasses is likely to depend on further parameters, e.g. the wind speed, mass of the animal and direction.

Some studies are designed in such a way that carcass persistence probability \( s \) and searcher efficiency \( f \) can be estimated from the carcass search data alone using mark-recapture models (Lebreton et al. 1992), see examples in Guinard et al. (2012) or Péron et al. (2013). The package carcass, however, is designed for studies where carcass persistence probability and searcher efficiency are estimated based on additional experiments, such as laying out trial carcasses to monitor their removal over time or to test naive observers. For such data, carcass may be used to estimate persistence probability and searcher efficiency, to subsequently combine these parameters into an estimate of the probability that an animal that has died during the study period is found by the observer \( p \), and to finally estimate the mortality \( N \) given \( p \) and the number of carcasses found \( c \).

The function persistence.prob estimates site-specific persistence probabilities based on experimental data. The function search.efficiency estimates the probability that a carcass that persisted is found by an observer. These two functions are wrappers of standard statistical methods. They are written for people with little experience in applying statistical models. However, before the functions are applied, please make sure that the data meet the model assumptions described below.

Estimates for carcass persistence probability and for searcher efficiency can be combined taking into account the design of the searches (how often and at what intervals the searches have been performed) to get an estimate of the
probability that a carcass that has fallen into the search area will be found. This has been done in different ways by different authors (Erickson et al. 2004, Shoenfeld 2004, Kerns et al. 2005, Jain et al. 2007, Pollock 2007, Huso 2010, Korner-Nievergelt et al. 2011, Etterson 2013, Péron and Hines 2014). The R-package carcass provides the methods presented by Korner-Nievergelt et al. (2011) and generalizations of these methods (Etterson 2013) that allow relaxing some of the assumptions made by the original method and Eq. 14 from Etterson (2013). Carcass also includes the method of Huso (2010). We do not give the theoretical background and do not test these methods via simulations here because this has been done in the specific studies.

There is no standard method that can be used in every case. Whether a method produces biased estimates or not depends on how well the data meet the implicit assumptions of the method chosen. Data sets can differ in a variety of aspects, such as number of carcasses found, length and regularity of search intervals, carcass persistence probability and its variability over time, searcher efficiency and its variability over time, design of the experiments to assess searcher efficiency and persistence probability, topography, spatial distribution of carcasses in relation to the search area etc. Such differences in methodology and experimental conditions induce that a statistical method that performs well in one study may produce a serious bias in another. Carcass is a collection of tools that help to individually design the analyses of carcass search data. To help to pick the most appropriate tools, we expanded the overview over the currently used methods from the review of Bernardino et al. (2013) and give some guidelines for when to choose which method below.

In addition to methods for the estimation of the detection probability $p$ (that a killed animal is eventually found), carcass also provides functions to estimate the number of animals that have died ($N$) given an estimate for $p$ and the number of carcasses found $c$. To do so, we use Bayes’ theorem. Carcass provides two functions for the estimation of $N$: 1) posteriorN calculates the posterior distribution of the number of fatalities given a detection probability estimate without taking into account the precision of the estimated detection probability. 2) estimateN does the same as posteriorN but accounts for uncertainty of the estimate of detection probability, using Monte Carlo simulations.

The methods provided by carcass allow users to estimate the total number of animals that have died, that is, summed over a specific (long) time span or spatial range assuming that mortality rate is constant. This is because the estimation of mortality based on a low number of carcasses, e.g. zero or one, is associated with very high stochastic uncertainty (see Discussion). Therefore, if more detailed estimates for the mortality rate are needed, e.g. daily or weekly mortality rates for single sites rather than the total number of animals killed over a long time period, we either have to collect the carcasses using a mark-recapture study design (Péron et al. 2013), or we could include additional information about the number of animals exposed to the hazard and use model based approaches as has been done by Bellebaum et al. (2013) and Korner-Nievergelt et al. (2013). The R-package fatalityCMR (Péron and Hines 2014) provides a model based approach to obtain mortality estimates.

To work with carcass basic knowledge of the R-language is required. If you are unfamiliar with the R-language, you may check out the internet tools <www.kollisionsopfersuche.uni-hannover.de> (in German; requires that the study design exactly follows Niermann et al. 2011), or <www.bio3.pt/en/services-and-projects/wildlife-fatality-estimator>, or the software provided by the USGS (Huso et al. 2012, Dalthorp et al. 2014).

How is carcass used?

Principal process

The following steps are necessary to estimate the number of fatalities from carcass searches.

1) Estimate the proportion of killed or injured animals that fall into the search area ($a$).
2) Estimate carcass persistence probability ($s$), if necessary for different ages of the carcass and different vegetation classes.
3) Estimate the probability that a carcass is found by an observer given it persists in the search area to the time of a search (searcher efficiency $f$), if necessary dependent on vegetation classes and dependent on the number of searches a carcass has already been exposed to.
4) Combine the parameters $a$, $s$ and $f$ with the search interval ($d$) or search schedule ($j$) to get the probability that an animal that has died is found (detection probability $p = f(a,s,f,d)$).
5) Estimate the number of animals that have died $N$ from the number of carcasses found ($c$) and the estimate for detection probability ($p$).

Load the package

```r
library(carcass)
```

Proportion of killed or injured animals that fall into the search area

The proportion of killed or injured animals that fall into the search area (and do not move away) is determined by the size and distribution of the area that can be searched, the spatial distribution of the carcasses, and the proportion of injured animals that move away from the study area before they die. If you can assume that all animals that have been killed have fallen into the area that has been searched (and that no additional carcasses dead from another cause lay in the search area), you can skip this chapter and use $a = 1$ later. However, often only parts of the area where carcasses fall into can be searched due to inaccessibility, time and funding constraints, or because of dangers such as traffic. In many studies, the proportion of carcasses that have fallen into the search area is far lower than the proportion of carcasses removed by scavengers prior to the search or the proportion of carcasses overlooked by an observer (Warren-Hicks et al. 2013, Huso and Dalthorp 2014). Therefore, $a$ is often among the most important parameters in terms of its influence on the resulting estimate of numbers of animals killed.

To obtain $a$ the spatial distribution of carcasses has to be combined with the spatial distribution of the search area. In many studies, carcass density decreases with distance to the obstacle (the cause of the hazard). Carcass density may,
therefore, be approximated by a function of distance from the obstacle. The density function of distance to the obstacle can be different in different directions depending on the shape of the obstacle, its height, prevailing wind directions and other factors. Carcass does not provide a general method that allows estimating a. Here, we only present an example of bat collisions at wind turbines to illustrate the principle of calculating a using information about the spatial distribution of carcasses from literature.

The data frame batdist contains examples of empirical and theoretical carcass distributions of bats at wind turbines (Table 1). The expected proportions of bats in each 10 m distance ring are given. Hull and Muir (2010) use a ballistic model to describe the spatial distribution below three different sizes of wind turbines for different carcass types and sizes, but the model does not seem to fit empirical data well (Arnett et al. 2005, Niermann et al. 2011, Huso and Dalthorp 2014). In addition, variation among sites and years may be substantial (Table 1). An empirical estimate of carcass distribution may be preferred (Dalthorp and Huso 2013).

To obtain the proportion of killed or injured animals that fall into the search area (a), we can, e.g. multiply the proportion that was searched in each of the 10 m distance rings with the proportion of carcasses found in the corresponding ring and sum over all rings. As an example, we use the bat distribution averaged over the first three studies in batdist and multiply these proportions with the proportions of the search area per ring. The latter proportions may be obtained using a geographic information system (GIS). When sites are heterogeneous regarding visibility class, it is preferable to use the proportions of carcasses falling into the different sub-units (e.g. distance rings) as weights when averaging detection probability p or any other parameter, such as f for s, over the whole site.

If the study species may move away from the wind turbine after collision, but before dying, we have to multiply the proportion of carcasses lying in the search area (obtained as described above) by 1 minus the proportion of animals that move out of the search area. For red kites Milvus milvus the proportion of individuals that move away from the turbine after collision may be up to 15 % (Bellebaum et al. 2013). We are not aware of estimates for other taxa.

### Carcass persistence time

Carcass persistence time is the duration a carcass stays on the ground before it is removed by scavengers or before it has decomposed (to a state that makes it essentially undetectable by the observers). Carcass persistence time depends primarily on the density and activity of scavengers, temperature and humidity. Thus, persistence time likely varies between sites. Carcass allows the estimation of carcass persistence probabilities for multiple study sites simultaneously.

To estimate carcass persistence time, individual carcasses have to be monitored over time to record the time until they disappear. Such time-to-event data are commonly analysed using survival models to estimate (daily) persistence probability.

Survival models differ in their assumption about how removal probability changes over time. Several studies found that persistence probability of carcasses increases over time, that is, fresh carcasses are removed with a higher probability than old carcasses (Van Pelt and Piatt 1995, Erickson et al. 2004, Ward et al. 2006, Warren-Hicks et al. 2013). Bispo et al. (2013) explore the fit of different parametric survival models to carcass removal data.

At present, two different models to estimate carcass persistence time are implemented in carcass:

1. the exponential model that assumes constant persistence probability over time,
2. the Cox proportional hazard model that allows for a changing persistence probability over time without making any assumption about the shape of the change.

But other survival models may be preferred (Bispo et al. 2013). From any survival analyses, either daily persistence probabilities or the proportion of carcasses that persist until every day after death (‘survivor function’) can later be used to estimate carcass detection probability.

Here, we first estimate daily carcass persistence probability s assuming a constant persistence probability. Second, we estimate separate daily persistence probabilities for each day after death. For both analyses, we will use the data set ‘persistence’. It contains persistence times in days for 636 brown mice and a few bat carcasses from 30 wind turbines. For each carcass, we know the persistence time in days (variable ‘persistence’) if the variable ‘status’ is 1, or we know the minimal persistence time if ‘status’ is 0 for carcasses that have not

<table>
<thead>
<tr>
<th>Study</th>
<th>Rotor</th>
<th>Nacelle</th>
<th>0–10m</th>
<th>10–20m</th>
<th>20–30m</th>
<th>30–40m</th>
<th>40–50m</th>
<th>&gt;50m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70</td>
<td>98</td>
<td>0.21</td>
<td>0.39</td>
<td>0.27</td>
<td>0.11</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>2a,b</td>
<td>72</td>
<td>80</td>
<td>0.10</td>
<td>0.26</td>
<td>0.28</td>
<td>0.26</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>2b</td>
<td>72</td>
<td>80</td>
<td>0.04</td>
<td>0.19</td>
<td>0.28</td>
<td>0.31</td>
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<td>0.04</td>
</tr>
<tr>
<td>3</td>
<td>66</td>
<td>65</td>
<td>0.30</td>
<td>0.26</td>
<td>0.20</td>
<td>0.15</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>80</td>
<td>0.24</td>
<td>0.23</td>
<td>0.19</td>
<td>0.15</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>3</td>
<td>110</td>
<td>94</td>
<td>0.21</td>
<td>0.20</td>
<td>0.18</td>
<td>0.15</td>
<td>0.12</td>
<td>0.14</td>
</tr>
</tbody>
</table>
disappeared until the last search (i.e. right-censored scavenging events). For example, the first brown mouse tested at turbine 5 (see first line in example data) was present at day 1 and day 2 after its placement (at day 0) but disappeared between day 2 and 3, i.e. the disappearance was observed (status = 1) at day 3. Another mouse, on line 7, persisted until the last control on day 14. Therefore, its persistence time is 14 and the status is 0 (disappearance not observed). Note that the persistence times are not known exactly because a scavenging event can hardly be observed directly, but it can be recorded that the carcass has disappeared between the last and present control. The models presently implemented in carcass assume that status = 1 means that the disappearance is exactly known. Therefore, when the time between two controls is large, other methods (e.g. allowing for interval-censoring) may be preferred.

When we assume a constant persistence probability, we fit an exponential survival model persistence.prob and obtain one estimate for persistence probability per turbine (or site). The argument pers.const TRUE is used to tell R that we assume a constant persistence probability.

The function returns a data frame with one row per site, the estimated daily persistence probability with the lower and upper limit of the 95% confidence interval, as well as the mean persistence time in days.

When we cannot assume a constant persistence probability, we may use the Cox proportional hazard model by setting the argument pers.const FALSE (i.e. the default).

The persistence probabilities estimated above are probabilities that a carcass persists for a given time interval, e.g. 24 hours. However, to estimate carcass detection probability, the relevant parameter is the proportion of persisting carcasses from all carcasses that arrived during a specific time interval. Thus, the estimates above can be used only if all carcasses arrive at the beginning of each time interval. Such
an assumption may be realistic for bat carcasses since often the majority of the bat carcasses arrive in the hour after sunset (Niermann et al. 2014). However, in other situations, carcasses may arrive continuously. If we assume a constant arrival rate, the persistence probabilities can be integrated over the last time interval to obtain the proportion of carcasses persisting until the end of the time interval.

Searcher efficiency is the probability that an observer finds a carcass that is in the search area at the time of the search. Searcher efficiency depends on experience of the observer, characteristics of the ground (particularly vegetation density influencing visibility), and type of object that is searched for. Furthermore, the average searcher efficiency often decreases with the number of searches the objects have been exposed to, because decaying carcasses are harder to find and because highly detectable objects will be found earlier than hidden objects. For example objects that have fallen into a hole will remain longer on the search area (Huso 2010).

Note that this integration is done automatically in the function `estimateN` when the argument ‘arrival’ is set to ‘uniform’.

**Searcher efficiency**

Searcher efficiency is the probability that an observer finds a carcass that is in the search area at the time of the search.
Such trials yield data similar to the data in the data frame searches:

```
data(searches)
searches
  person visibility detected notdetected
1   NameA     open       4         0
2   NameB     open       1         0
3   NameC     open       4         1
4   NameD     open       2         0
5   NameE     open       5         1
6   NameF     open       1         1
7   NameA   overgrown     2         0
8   NameB   overgrown     12        0
9   NameC   overgrown     3         0
10  NameD   overgrown     1         0
11  NameE   overgrown     0         1
12  NameF   overgrown     2         1
13  NameA heaviy_overgrown    2        1
15  NameB  heavily_overgrown    4        0
16  NameE  heavily_overgrown    1        1
17  NameF  heavily_overgrown    7        2
```

The example data was collected by Niermann et al. (2011). It contains the number of detected and undetected items for each of nine observers (variable 'person') and three visibility classes of the ground. The function search.efficiency estimates searcher efficiency \( f \) for each person and visibility class, as well as for each visibility class averaged over all persons. The average may be useful, if trial data on searcher efficiency are missing for some persons in the study. The function search.efficiency uses the function glmer from the package lme4 (Bates 2005) to fit a generalized linear mixed model with binomial error distribution and logit link function to model the number of detected and not detected items. From this model the fitted values (search efficiency) are extracted for each person and visibility class as well as for every visibility class averaged over all the persons. Visibility is used as a fixed effect and person as a random effect. When the data are limited to only one or two observers, observer is also treated as a fixed effect, and a generalised linear model is fitted by the function glm from the stats-package. Treating person as a random factor in the model has the advantage that for persons with a low number of experimental data (i.e. weak information about their searcher efficiency) the estimate is shrunk towards the overall mean. In this way we avoid large over- or underestimation of person-specific searcher efficiencies that are due to the stochasticity of the experimental data (Gelman and Pardoe 2006).

To estimate searcher efficiency using search.efficiency one must provide the data (i.e. observer id, visibility for each trial, number of detected and not detected items) either bundled in a data frame or as separate vectors. If the function is applied to a data frame, this data frame must contain the following four variables with the exact names: 'person', 'visibility', 'detected', 'notdetected' (spelling and capitalization is important!). If data for only one visibility class is available (or visibility class has not been recorded), the variable 'visibility' has to contain the same value on each line. The function allows two (and only two) categorical explanatory variables (visibility class and observer id), thus it is not possible to include other explanatory variables or covariates.

The precision of the estimated search efficiency \( f \) is obtained using Bayesian methods, because these methods are more reliable in generalised linear mixed models than frequentist methods (Bolker et al. 2009). The function simulate from the package arm is used to sample from the joint posterior distribution of the model parameters (Gelman and Hill 2007). The 2.5% and 97.5% quantiles of the random draws from the posterior distributions are used as lower and upper limits of the 95% credible intervals. The number of random draws can be specified in the argument nsim. Default is 1000, but higher numbers are recommended for reliable credible intervals.

The models used by search.efficiency assume that the number of detected items is binomially distributed within each observer and visibility class. If the data are aggregated so that there is one row for each combination of observer and visibility class and visibility class has the same effect on searcher efficiency for each observer (no interaction between observer and visibility class), there is little danger of violating this assumption. However, if the observers have been tested in different trials so that there are two or more rows per observer and visibility class, the variance in the data may be higher than assumed by the binomial model (overdispersion). If overdispersion is likely to be present, the models have to be fitted 'by hand' using the functions glm or glmer and checked for overdispersion as, e.g. described in Gelman and Hill (2007).

In real data, different sub-units (areas) will have different visibility classes with different corresponding searcher efficiencies and, often, also different persistence probabilities (Warren-Hicks et al. 2013). In such cases, it may be best to calculate the detection probability \( p^*_k \) for every sub-unit \( (1,...,K) \) separately. The weighted average of the detection probabilities \( p^*_k \) with weights equal to the proportion of carcasses falling into the different sub-units \( a_k \) can serve as an overall detection probability \( p \). Dalthorp et al. (2014) explain how to calculate the variance for this weighted average. For simplicity, we here assume that only one visibility class was present.

**Combining the proportion of carcasses in the search area \( a \), persistence probability \( s \) and searcher efficiency \( f \) to get the detection probability \( p \)**

The probability that an animal that has died is eventually found by an observer \( (p) \) is related to the proportion of carcasses that have fallen into the search area \( (a) \), the persistence time \( (s) \) and the searcher efficiency \( (f) \). These three parameters have been combined in various different ways to get \( p \). Table 2 gives an overview over the commonly used methods.

First, some methods assume that the searches have been done regularly (constant search interval). If the searches have been done at irregular time intervals, average search interval can be used. However, if the search interval is large compared to the carcass persistence time, mortality will be underestimated because during longer than average search intervals some carcasses will disappear without having the chance of being detected during any search. In such cases, it is prudent to use a method that allows for irregular search intervals.

Second, many studies on carcasses found that fresh carcasses are removed by scavengers with higher probability than old carcasses (Van Pelt and Piatt 1995, Ward et al. 2006, Bispo et al. 2013, Warren-Hicks et al. 2013). Therefore, it is better to use methods that allow for age-dependent persistence probabilities, if sample size is sufficient to estimate age-dependent persistence probabilities. It may not be important to account for changing persistence times with carcass age when search intervals are short compared to persistence time.
times and searcher efficiency is high. In some studies change in persistence time with calendar date may be more important than with carcass age, e.g. when temperature or humidity substantially changed or scavengers arrived. Then the formula developed by Etterson (2013) will be a good choice.

Third, some methods do not take into account that carcasses that have been overlooked during one search can be found during subsequent searches (‘bleed-through’). Therefore, for data sets with long persistence times (relative to the search interval) and low searcher efficiency (where a high proportion of carcasses can be expected to be overlooked during the first search and found during subsequent searches) it is recommended to use a method that accounts for this situation (which may often be the case, thus bleed-through should mostly be accounted for) such as Kerns et al. (2005), Korner-Nievergelt et al. (2011) or Etterson (2013).

Fourth, if searcher efficiency is likely to change with the number of searches a carcass was exposed to or with its age the choice should be one of the methods that allow for variable searcher efficiency. This may be particularly important on heterogeneous terrain, where some carcasses fall into holes and others not, or when some animals are injured and seek cover prior to dying. In such cases, the average detectability of a carcass in a cohort decreases with the number of searches they were exposed to because easy to detect carcasses are found first. Carcass detectability may also decrease due to decay of the carcasses, i.e. dependent on carcass age, or change with calendar date, e.g. due to vegetation growth.

At present, the package carcass provides the following different methods to calculate \( p \): Huso’s estimator (Huso 2010), the formula we developed earlier (Korner-Nievergelt et al. 2011) including some extensions, and the recently published formulae by Etterson (2013). The methods currently provided by carcass are summarized in Table 3. The formula presented by Huso (2010) and implemented in the software Huso et al. (2012) require a mean persistence time estimates from a parametric model such as an exponential or Weibull model. The formula Korner-Nievergelt et al. (2011) assumes constant persistence probability and constant or decreasing searcher efficiency. In the package carcass we extend the formulas published in Korner-Nievergelt et al. (2011) to allow for time variation (based on parametric or non-parametric models) of persistence probabilities (Supplementary material Appendix 1). The formulas by Etterson (2013) are based on the same model as the one in Korner-Nievergelt et al. (2011).

### Table 3: \( p \) Estimates using various methods

<table>
<thead>
<tr>
<th>Visibility</th>
<th>Person</th>
<th>Mean Persistence</th>
</tr>
</thead>
<tbody>
<tr>
<td>heavily overgrown</td>
<td>NameA</td>
<td>0.8185871</td>
</tr>
<tr>
<td>open</td>
<td>NameA</td>
<td>0.8770466</td>
</tr>
<tr>
<td>heavily overgrown</td>
<td>NameB</td>
<td>0.8365675</td>
</tr>
<tr>
<td>open</td>
<td>NameB</td>
<td>0.8900113</td>
</tr>
<tr>
<td>heavily overgrown</td>
<td>NameC</td>
<td>0.7835797</td>
</tr>
<tr>
<td>open</td>
<td>NameC</td>
<td>0.8512704</td>
</tr>
<tr>
<td>heavily overgrown</td>
<td>NameD</td>
<td>0.7938000</td>
</tr>
<tr>
<td>open</td>
<td>NameD</td>
<td>0.8010652</td>
</tr>
<tr>
<td>heavily overgrown</td>
<td>NameE</td>
<td>0.8106593</td>
</tr>
<tr>
<td>open</td>
<td>NameE</td>
<td>0.8464808</td>
</tr>
<tr>
<td>heavily overgrown</td>
<td>NameF</td>
<td>0.7567780</td>
</tr>
<tr>
<td>open</td>
<td>NameF</td>
<td>0.8310441</td>
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<tr>
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<td>0.8201803</td>
</tr>
<tr>
<td>open</td>
<td>NameG</td>
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</tr>
<tr>
<td>open</td>
<td>NameI</td>
<td>0.8239952</td>
</tr>
</tbody>
</table>

\[ f \leftarrow \text{search.f}\$f \leftarrow \text{search.f}\$f.\text{average}\$f[1] \]
\[ f.\text{lower} \leftarrow \text{search.f}\$f.\text{average}\$lwr[1] \]
\[ f.\text{upper} \leftarrow \text{search.f}\$f.\text{average}\$upr[1] \]
Table 2. Overview over the most commonly used methods to estimate mortality from carcass searches (using unmarked carcasses). For every method, assumptions regarding the regularity of the search interval, the carcass persistence probability, and searcher efficiency are given. The 5th column indicates whether the method accounts for carcasses that are not found during one search but found in subsequent searches (termed ‘bleed-through’ by Warren-Hicks 2013). The last column names software with the specific method implemented. The first part of the table (“Formulas”) contains methods that first estimate the probability that a killed animal is found and, subsequently, use the total number of carcasses found together with the estimated detection probability to get a mortality estimate, e.g. a Horvitz–Thompson estimate or a posterior distribution using Bayes’ theorem. The second part of the tables (‘Models’) contains statistical models that are fitted to the raw search data (number of carcasses found for every single search) taking detection probability into account. The table is adapted from Bernardino et al. (2013).

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Search interval</th>
<th>Persistence probability</th>
<th>Searcher efficiency</th>
<th>Carcass not found during a search can be found in a subsequent search</th>
<th>Software</th>
</tr>
</thead>
<tbody>
<tr>
<td>Formulas</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shoenfeld 2004 (Eq. 4/5) = Erickson et al. 2004 (p. 8)</td>
<td>search intervals are Poisson-distributed with mean search interval d</td>
<td>removal times follow a Poisson or an Exponential distribution</td>
<td>?</td>
<td>yes but assumes 100% bleed-through (Warren-Hicks 2013)</td>
<td>- R-package carcass</td>
</tr>
<tr>
<td>Kerns et al. 2005 (Eq. 6/7)</td>
<td>regular</td>
<td>?</td>
<td>constant</td>
<td>yes</td>
<td>Wildlife Fatality Estimator (&lt;www.bio3.pt&gt;)</td>
</tr>
<tr>
<td>Jain et al. 2007 (Eq. 8)</td>
<td>no explicit assumptions</td>
<td>constant</td>
<td>?</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Pollock 2007 (Eq. 8/9)</td>
<td>regular</td>
<td>number of verifications before removal follows a geometric model</td>
<td>?</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Huso et al. 2012</td>
<td>regular or irregular</td>
<td>constant or depending on carcass age</td>
<td>constant or time variable</td>
<td>no</td>
<td>Huso et al. (2012)</td>
</tr>
<tr>
<td>Korner-Nievergelt et al. 2011 (Eq. 11/12)</td>
<td>regular</td>
<td>constant</td>
<td>constant or depending on the number of searches per carcass (i.e. carcass age)</td>
<td>yes</td>
<td>- R-package carcass - Wildlife Fatality Estimator (&lt;www.bio3.pt&gt;) - &lt;www.kollision-sopferutsche.uni-hannover.de&gt;</td>
</tr>
<tr>
<td>this article</td>
<td>regular</td>
<td>constant or depending on carcass age (any survival function)</td>
<td>constant or decreasing exponentially with the number of searches per carcass (i.e. carcass age)</td>
<td>yes</td>
<td>- R-package carcass</td>
</tr>
<tr>
<td>Etterson 2013</td>
<td>regular or irregular</td>
<td>constant or depending on carcass age or dependent on calendar date</td>
<td>constant or dependent on number of searches per carcass or dependent on calendar date</td>
<td>yes</td>
<td>- R and Matlab code in electronic supplement - R-package carcass</td>
</tr>
<tr>
<td>Dalthorp et al. 2014</td>
<td>regular or irregular</td>
<td>one of several potential parametric survival models: Weibull, loglogistic, lognormal, exponential</td>
<td>constant or depending on carcass age</td>
<td>Yes</td>
<td><a href="http://pubs.er.usgs.gov/publication/ds881">http://pubs.er.usgs.gov/publication/ds881</a></td>
</tr>
<tr>
<td>Models</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Korner-Nievergelt et al. 2013</td>
<td>regular or irregular</td>
<td>constant*</td>
<td>constant*</td>
<td>yes</td>
<td>- Bugs code in electronic supplement - R-package fatality CMR</td>
</tr>
<tr>
<td>Péron et al. 2013</td>
<td>regular or irregular (but for all sites the same sampling protocol has to be used)</td>
<td>constant or different between two classes (e.g. ‘fresh’ and ‘old’) of the carcasses</td>
<td>constant or different between age classes (e.g. ‘fresh’ and ‘old’) of the carcasses</td>
<td>yes</td>
<td>R and Matlab code in electronic supplement</td>
</tr>
<tr>
<td>Péron and Hines 2014</td>
<td>regular or irregular requires double searches and marking of carcasses</td>
<td>constant or time dependent*</td>
<td>constant or depending on carcass age*</td>
<td>yes</td>
<td>R and Matlab code in electronic supplement</td>
</tr>
<tr>
<td>Etterson 2013</td>
<td>regular or irregular</td>
<td>Weibull (including exponential)</td>
<td>constant or depending on carcass age and number of searches per carcass</td>
<td>yes</td>
<td>R-package in preparation</td>
</tr>
</tbody>
</table>

*The model code can be adapted to allow for any survival function or for any relationship of searcher efficiency with carcass age or the number of searches a carcass has experienced. The model based approach allows including covariates for any model parameters.
Table 3. Overview of the functions currently provided by carcass for calculating the carcass detection probability \( p \) from persistence probability \( s \), searcher efficiency \( f \), and optional additional information such as search interval \( d \) or a vector of lengths of search intervals of different lengths \( J \). All functions, except \text{phuso} account for bleed-through (Table 2).

<table>
<thead>
<tr>
<th>Search interval</th>
<th>Searcher efficiency</th>
<th>Persistence probability</th>
<th>Function in carcass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular</td>
<td>constant</td>
<td>constant</td>
<td>\text{phuso}</td>
</tr>
<tr>
<td></td>
<td>decreasing with number of searches</td>
<td>constant</td>
<td>\text{etterssonEq14}</td>
</tr>
<tr>
<td>Regular</td>
<td>constant</td>
<td>dependent on age of carcass (input: 'survivor curve')</td>
<td>\text{pkorner}</td>
</tr>
<tr>
<td>Regular</td>
<td>decreasing with number of searches</td>
<td>dependent on age of carcass (input: 'survivor curve')</td>
<td>\text{pkorner}</td>
</tr>
<tr>
<td>Irregular</td>
<td>constant</td>
<td>constant or dependent on calendar date</td>
<td>\text{etterssonEq14}</td>
</tr>
<tr>
<td>Irregular</td>
<td>constant or dependent on the number of searches</td>
<td>constant or dependent on age of carcass (input: daily persistence probability)</td>
<td>\text{etterssonEqv2}</td>
</tr>
</tbody>
</table>

A mathematical proof that Eq. 15 of Etterson (2013) is equivalent to the formula Korner-Nievergelt et al. (2013) is given in Supplementary material Appendix 2. Etterson (2013) provided a generalization of this formula that allows for irregular search intervals. He further provides two different variants of time dependence in searcher efficiency and persistence probability (on carcass age or calendar date).

Detection probability \( p \) is a function \( f(s, f, a, d, n) \), where \( s \) is the persistence probability, \( f \) the searcher efficiency, \( a \) the proportion of carcasses that have fallen into the search area, \( d \) the search interval (usually in days), and \( n \) the number of searches. In case of irregular search intervals, a vector with the length of the search intervals \( J \) is used instead of \( d \) and \( n \). The factor \( a \) affects \( p \) in a simple multiplicative way, therefore, we can write \( p^* = f(s, f, d, n) \), or \( p^* = f(s, f, J) \) respectively, and \( p = a p^* \).

### Calculation of \( p^* \) assuming constant persistence and constant searcher efficiency

Let's assume that searcher efficiency \( f \) and persistence probability \( s \) are constant. Then we use either of the functions \text{phuso}, or \text{pkorner} for regular search intervals or \text{etterssonEq14} for irregular search intervals.

The function \text{phuso} is based on the average persistence time \( t \) which is \( 1/\log(s) \) in the case of a constant persistence probability. We can either provide \( s \) or \( t \). The search interval \( d \) has to be provided in addition to \( s \) and \( f \). For \text{pkorner} we have to provide the total number of searches \( n \) in addition (\( dn \) is then the length of the study period), and \text{etterssonEq14} requires a vector with the lengths of the search intervals.

The function \text{pkorner} provides 95% confidence intervals of the detection probability if the argument CI is set to TRUE and lower and upper limits of \( s \) and \( f \) are given. These confidence intervals are obtained by Monte Carlo simulations.

```r
pkci <- pkorner(s=s, s.lower=s.lower, s.upper=s.upper, f=f, f.lower=f.lower, f.upper= f.upper, d=2, n=100, CI=TRUE)
```

For the result of \text{etterssonEq14} a Monte Carlo confidence interval can be calculated by the function \text{CIettersson}.

```r
CIettersson(s=s, s.lwr=s.lower, s.upr=s.upper, f=f, f.lwr=f.lower, f.upr=f.upper, J=J)
```

The function \text{etterssonEq14} can handle irregular search intervals.

```r
J <- c(3,5,4,2,1,4,4,5,6,2,3,4,5,3,2)
etterssonEq14(s=s, f=f, J=J)
```

Note that when defining a constant \( s \), it is assumed that carcasses arrive only at the beginning of each time interval. To account for continuous carcass arrival, the survivor function (proportion of persisting carcasses for each day after death) has to be integrated over each time interval and the formulas allowing for time variable persistence probabilities used (use 'sca' instead of 'vars' below).
The function `ettersonEq14v1` allows for searcher efficiency that depends on calendar date. For example, the searches started in high and dense crop where searcher efficiency was low and after half-time of the study the crop was cut so that searcher efficiency suddenly increased.

For the confidence intervals, use `CIetterson`. The function `phuso` does not allow one to specify the factor of the decrease in searcher efficiency with each search, but it seems to be fairly robust with respect to a decrease in searcher efficiency (Huso 2010, Korner-Nievergelt et al. 2011), and the new software Huso (2012) and Dalthorp et al. (2014) also allows for time dependence in searcher efficiency.

**Calculation of \( p^* \) assuming constant persistence probability and time-variable searcher efficiency**

If the detectability differs between the carcasses, e.g. because some carcasses have fallen into a hole whereas others are exposed, the average detectability of a cohort of carcasses will decrease with the number of searches they were exposed to. This is because easily detectable carcasses will be found during earlier searches whereas hard to detect carcasses remain on the ground. Huso (2010) suggests that the decrease in average detectability with each search may be as high as 75%. The function `pkorner` permits modelling such a decrease by setting the argument `search.efficiency.constant=FALSE`. The argument \( k \) allows one to specify the factor by which the searcher efficiency \( f \) (of a cohort of carcasses) is multiplied at each search (that the cohort is exposed to). The mathematical derivation of this formula is given in the Supplementary material Appendix 1.

If the argument `CI` is set to `TRUE`, a 95% confidence interval is calculated using Monte Carlo simulations.

```r
pk <- pkorner(s=s, f=f, d=2, n=100, search.efficiency.constant=FALSE, k=0.25)
pk
[1] 0.5928075

pkci <- pkorner(s=s, s.lower=s.lower, s.upper=s.upper, f=f, f.lower=f.lower, f.upper= f.upper, d=2, n=100, search.efficiency.constant=FALSE, k=0.25, CI=TRUE, nsim=100)
pkci # a higher number of Monte Carlo simulations (nsim) is recommended
   p 2.5% 97.5% 0.5928075 0.404781 0.7644495
```

The function `ettersonEq14v2` allows specifying different searcher efficiencies for all possible number of searches a carcass has been exposed to. For example, when detectability of a carcass is high during the first search and then drops markedly, because the easy to detect carcasses are found during the first search but later the change in average detectability between two searches may vanish, this pattern can be specified by a vector that contains the searcher efficiency for every search separately. Note that persistence probability needs to be specified for every possible age of a carcass in the study.

Searcher efficiency can also decrease with age of the carcass. To account for age-dependent searcher efficiency is not yet implemented. However, in case of regular (and short) search intervals, carcass age corresponds to the number of searches a carcass has been exposed to, and `ettersonEq14` or `pkorner` may be applied. The R-package `carcass-CMR` (Péron and Hines 2014) can estimate searcher efficiency dependent on two age classes (old versus fresh). The R-package that is currently under development by R. Wolpert (Table 2) will be able to account for searcher efficiency that depends on age and the number of searches a carcass has been exposed to.

```r
fperdate <- c(0.4, 0.4, 0.4, 0.4, 0.9, 0.9, 0.9, 0.9)
j <- c(3, 5, 2, 4, 4, 5, 2)
ettersonEq14v1(s=rep(s, sum(j)), f=fperdate, j=j)
[,1] 0.4772668
```

For the confidence intervals, use `CIetterson`. The function `phuso` does not allow one to specify the factor of the decrease in searcher efficiency with each search, but it seems to be fairly robust with respect to a decrease in searcher efficiency (Huso 2010, Korner-Nievergelt et al. 2011), and the new software Huso (2012) and Dalthorp et al. (2014) also allows for time dependence in searcher efficiency.

**Calculation of \( p^* \) assuming time-variable persistence and constant searcher efficiency**

The functions `pkorner` and `ettersonEq14v2` can deal with persistence probabilities that vary with the age of the carcass. `pkorner` takes the proportion of remaining carcasses for each day after death in a vector as input (i.e. the 'survivor curve'; output of `persistence.prob` with non-constant persistence), whereas `ettersonEq14v2` takes a vector with daily persistence probabilities for every possible age class.

```r
fpersearch <- c(0.9, 0.2, 0.18, 0.15, 0.15, 0.15, 0.15, 0.15)
j <- c(3, 5, 2, 4, 4, 5, 2)
ettersonEq14v2(s=rep(s, sum(j)), f=fpersearch, j=j)
[,1] 0.5542363
```

For the confidence intervals, use `CIetterson`.
carcass age. Both functions cannot handle missing values, thus these need to be imputed.

If the argument CI is set to TRUE, a 95% confidence interval is calculated using Monte Carlo simulations.

To use the function `ettersonEq14v2`, e.g. because search intervals were irregular, the daily persistence probabilities instead of the survivor curve has to be given. Here, we extract the daily persistence probabilities from the survivor curve and impute the missing values for the carcasses with age higher than 14 days with the estimate for day 14.

```
nonconstant.s <- vars$persistence.prob[,1]
nonconstant.s
     1     2     3     4     5     6     7
0.76865162 0.58393492 0.47539667 0.36678317 0.28594559 0.22125794 0.1912215
     8     9    10    11    12    13    14
0.16330202 0.13298274 0.12482560 0.10244159 0.08000630 0.07153021 0.0605884
# check whether proportion of remaining carcasses is estimated for every consecutive day (whether there are missing values):
vars$time
[1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14
nonconstant.s.lower <- vars$lower[,1]
nonconstant.s.upper <- vars$upper[,1]

pk <- pkorner(s=nonconstant.s, f=f, d=2, n=100)
pk
 [1] 0.6143254

pkci <- pkorner(s=nonconstant.s, s.lower=nonconstant.s.lower, s.upper=nonconstant.s.upper, f=f, f.lower=f.lower, f.upper=f.upper, d=2, n=100, CI=TRUE, nsim=100) # higher values for nsim are recommended
pkci
 p   2.5%  97.5%
0.6143254 0.49007620 0.7278280
```

Calculation of p* assuming time-variable persistence and time-variable searcher efficiency

We can allow for both decreasing searcher efficiency with the number of searches a carcass was exposed to and time-variable persistence for regular (`pkorner` or `ettersonEq14v2`) and irregular (`ettersonEq14v2`) search intervals.

Again, it is possible to specify `CI = TRUE` to obtain a 95% confidence interval. And, again, we recommend using more than the 100 simulations (> 2000) given in the example code.

```
J <- c(3,2,5,2,4,4,5,2)
dailys <- numeric(sum(J))
dailys[1] <- nonconstant.s[1] # day 1
for(i in 2:length(nonconstant.s)) dailys[i] <- nonconstant.s[i]/nonconstant.s[i-1]
# use the last estimate for persistence probability for the missing values
     dailys[length(nonconstant.s)+1]:sum(J)] <- dailys[length(nonconstant.s)]

ettersonEq14v2(s=dailys, f=rep(f,length(J)), J=J)
 [1,] 0.4915348
```

If daily persistence probability depends on calendar date rather than carcass age, the function `ettersonEq14v1` is used.

```
J <- c(3,2,5,2,4,4,5,2)
# For example, after the first 15 days of the study, a fox detected the sources of carcasses:
sperdate <- c(rep(0.8, 15), rep(0.4, 12))

ettersonEq14v1(s= sperdate, f=rep(f,length(J)), J=J)
 [1,] 0.3352823
```

Also, for the last two estimates, confidence intervals can be calculated using the function `CIetterson`.

```
J <- c(3,2,5,2,4,4,5,2)
```

Or, when both persistence probability and searcher efficiency depend on calendar date:
And confidence intervals for the estimates obtained by the formulas of Etterson (2013) are calculated by CI etterson.

Last important step to obtain p
Finally, we have to combine the probability that a carcass that has fallen into the search area is found by an observer \( p \) with the proportion of carcasses that have fallen into the search area \( a \) to obtain the probability that an animal that has died during the study period is found by an observer \( p \). In the simple example used here with one visibility class only (\( p \) is equal for all sub-units of the search area), \( p \) is the product \( p \cdot a \). When \( p \) differs between sub-units (e.g. due to different visibility classes), \( p \) is a weighted average of the sub-unit-specific \( p \) with weights equal to the proportions of carcasses within the different sub-units (\( a \), see section ‘Searcher efficiency’).

Estimate the number of animals that have died (N)
Assuming that \( a \) is constant over time and that no carcass has been present at day one of the study (which is the day of the first search minus the search interval \( d \)), the probability \( p \) is used to estimate the number of animals that have died \( \hat{N} \) from the number of carcasses found \( c \). The method implemented in carcass is using Bayes’ Theorem with a uniform prior distribution (Korner-Nievergelt et al. 2011, Niermann et al. 2011). Thereby, for any \( x \), the probability that \( N \) equals \( x \) is given by:

\[
P(N = x) = \frac{x}{c} \left( \frac{1-p}{(1-p)^{x-c}} \right)
\]

If we assume that the detection probability \( p \) is known (without error), we use the function posteriorN. The function returns the probability for each possible value of \( N \) given \( c \) (argument nf, number found) and \( p \), if the argument dist = TRUE. If dist = FALSE, the function returns the median of the posterior distribution (expected) and the 2.5% and 97.5% quantiles (95% credible interval). The Horvitz–Thompson (Horvitz and Thompson 1952) estimate (HT.estimate) equals the number of carcasses found divided by \( p \).

To take into account the error in the estimate of \( p \) we can use the function estimateN. This function uses Monte Carlo simulation to propagate the uncertainty of \( p \) to the estimate of \( N \), as presented in the worked example in Korner-Nievergelt et al. (2011).

The message tells us what assumptions are made concerning the arrival of the carcasses and the time dependence of the carcass persistence probability and how we could change this if needed. Further, it plots the posterior distribution of the number of dead animals if the argument plot is set to TRUE (Fig. 2). The argument pform is one of ‘etterson’, ‘huso’ or ‘korner’. In the argument ‘x’ it is specified which posterior probabilities \( P(\text{number of animals killed} > x) \) are given in the output.

Thus, for turbine 1 with three carcasses found by the observers, we conclude based on the estimates for the proportion of carcasses that have fallen into the search area \( \hat{a} = 0.67 \), the daily persistence probability \( \hat{s} = 0.80 \), and the searcher efficiency \( \hat{f} = 0.79 \) that the true number of fatalities must be around 7 with a 95% credible interval of 3–18, taking into account the uncertainties in the estimates \( s \) and \( f \).

Figure 2. Posterior distribution of the number of fatalities.
estimateN(3, f = f, f.lower = f.lower,
    f.upper = f.upper,
    s = s, s.lower = s.lower, s.upper = s.upper, a = a,
    pform = "korner", d = 2, n = 100, plot=FALSE, x=c(5, 10, 20))

You assume that all carcasses arrive simultaneously
once a day right after the time the search takes place (if there is one)
and that the probability to persist from death to the first day
(the time the searches normally are performed) is equal to the probability
to persist from one day to the next. To change that,
use a different persistence probability for the first day
or choose arrival='uniform' to allow carcasses to arrive continuously.
$estimate
[1] 7

$lower
[1] 3

$upper
[1] 18

$HT.estimate
[1] 6.818126

$P.true.larger.x
x=5  x=10  x=20
0.74998722 0.22799419 0.01075105

$O.estimate
[1] 4

$O.lower
[1] 2

$O.upper
[1] 6

$HT.O.estimate
[1] 2.409061

$P.true.larger.O.x
x=5  x=10  x=20
0.74998722 0.22799419 0.01075105

f. Or: there is only a small probability (of 0.01) that the true
number of fatalities was larger than 20.

Discussion

Unlike in approaches based on stochastic models, as pro-
vided in the R-package fatalityCMR (Péron et al. 2013)
or presented in Etterson (2013) and Korner-Nievergelt et al.
(2013), there is no formal method to assess whether the
model assumptions are met or to do model selection, since
the methods implemented in carcass are deterministic for-
mulas rather than stochastic models that are fit to the data.
No likelihood or other measure of model fit exists for such
formulas. Therefore, it is important to decide whether time
or age dependent persistence times or searcher efficiency are
needed at the time when these parameters are estimated, e.g.
by plotting the observed proportion of persisting carcasses
over time together with the model estimates (as in Fig. 1). To
assess whether searcher efficiency depends on carcass age, the
search efficiency experiments have to be done with carcasses
of different ages and its influence on searcher efficiency has
to be analysed in separate analyses. Similarly, effects of calen-
dar date need to be investigated for each single study.

Mortality estimates based on carcass searches can be very
uncertain especially when the number of carcasses found
and detection probability are low. In a simulation study, we
showed that the relative error in the point estimate for mortal-
ity strongly increases when the number of carcasses found
is lower than 10 (Korner-Nievergelt et al. 2011). A consequence
of the high uncertainty of estimates for \( \hat{N} \) based on a low
number of carcasses found is that sums of \( \hat{N} \) (e.g. over many
wind turbines within a wind park) will overestimate the total num-
ber of fatalities for the whole wind park. In such a case, we
recommend estimating the total number of fatalities based on
the sum of the turbine-specific counts using an average detec-
tion probability rather than summing the single turbine-spe-
cific estimates \( \hat{N} \), or use the posterior probability that the true
number of fatalities does exceed a specific number instead of
the point estimate. Alternatively, a fully model based approach
could allow estimation of turbine specific fatality rates based
on a data set pooled over several turbines (Bellebaum et al.

The aim of the functions provided by carcass (listed in Table 3)
is to provide easy to apply mortality estimators while taking
the most important variance in carcass persistence time and
searcher efficiency into account. As often, there is a tradeoff
between simplicity and flexibility. The methods will perform
well as long as the data meets the underlying assumptions,
explained in Table 3 and the text. However, if the data shows a
higher complexity, e.g. when persistence probability simulta-
neously depends on calendar date and age of the carcass, mor-
tality estimates will be more precise when using more complex
models such as done by Bellebaum et al. (2013), Etterson
(2013), Korner-Nievergelt et al. (2013) or Péron et al. (2013).
Nevertheless, carcass provides a variety of different methods
that can be combined in a flexible way. The user can choose in
each step of the analysis the most appropriate model for the
specific study to reduce bias in the mortality estimation.

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Any use of trade, firm, or product names is for descriptive purposes
only and does not imply endorsement by the U.S. Government.

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