



THE UNIVERSITY *of* EDINBURGH

Edinburgh Research Explorer

Can Managers Inform Models? Integrating Local Knowledge into Models of Red Deer Habitat Use

Citation for published version:

Irvine, RJ, Fiorini, S, Yearley, S, McLeod, JE, Turner, A, Armstrong, H, White, PCL & Wal, RVD 2009, 'Can Managers Inform Models? Integrating Local Knowledge into Models of Red Deer Habitat Use', *Journal of Applied Ecology*, vol. 46, no. 2, pp. 344-352. <https://doi.org/10.1111/j.1365-2664.2009.01626.x>

Digital Object Identifier (DOI):

[10.1111/j.1365-2664.2009.01626.x](https://doi.org/10.1111/j.1365-2664.2009.01626.x)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Early version, also known as pre-print

Published In:

Journal of Applied Ecology

Publisher Rights Statement:

© Irvine, R. J., Fiorini, S., Yearley, S., McLeod, J. E., Turner, A., Armstrong, H., White, P. C. L., & Wal, R. V. D. (2009). Can Managers Inform Models? Integrating Local Knowledge into Models of Red Deer Habitat Use. *Journal of Applied Ecology*, 46(2), 344-352 doi: 10.1111/j.1365-2664.2009.01626.x

General rights

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.



1 **Can managers inform models? Integrating local knowledge into models of red**
2 **deer habitat use.**

3 R. J. IRVINE*, S. FIORINI*, S. YEARLEY†, J. MCLEOD*, A. TURNER#,
4 H.ARMSTRONG§, P. C. L. WHITE‡ & R. VAN DER WAL#

5 *Macaulay Institute, Aberdeen AB15 8QH, UK; #Aberdeen Centre for Environmental
6 Sustainability, University of Aberdeen, AB24 3UU, UK; § Forest Research, Roslin,
7 EH25 9SY, UK; †ESRC Genomics Forum, University of Edinburgh, EH8 8AQ, UK;
8 ‡Environment Department, University of York, YO10 5DD, UK
9

10 **Summary**

- 11 1. Many ecologically-based wildlife-habitat models provide only limited
12 explanations of the observed data because understanding of how the key
13 factors driving distribution interact with local management is not taken into
14 account. If models are to be credible tool for developing solutions for wildlife
15 management, they need to integrate scientific knowledge with the wealth of
16 knowledge held by those who manage these resources.
- 17 2. In this paper, we develop a participatory approach to integrate local
18 knowledge from deer managers with formal scientific understanding and
19 ecological spatial data in a simple GIS to predict red deer distribution in the
20 uplands of Scotland. We evaluate the extent to which the predictions are
21 improved by this process.
- 22 3. The initial GIS prediction matched managers' experience of deer locations and
23 fitted with independently-derived deer point count data in around 50% of all
24 cases.
- 25 4. Analysis of interviews with managers indicated that shelter provided by
26 habitat characteristics was more important than topographic shelter or the
27 forage value of the habitat. Disturbance, slope and elevation were also

1 important. Analysis of the underlying spatial characteristics of manager
2 defined areas preferred by deer indicated similar relative importance of these
3 factors in driving deer distribution.

4 5. The model was then modified to incorporate the managers' knowledge and
5 new predictions were evaluated against existing deer distribution data. The
6 match between point counts and areas predicted by the model as being highly
7 suitable for deer increased from around 50% to around 80%.

8 6. *Synthesis and applications.* Our evaluations demonstrate the validity of using
9 local knowledge which can substantially improve the predictions from simple
10 spatial models of deer habitat suitability. Our approach enables knowledge
11 from different sources and at different spatial scales to be combined to give
12 realistic predictions of deer distribution at an appropriate scale. Such a
13 participatory approaches to wildlife-habitat model development has the
14 potential to improve communication and consensus across ownership
15 boundaries where different management objectives exist.

16 *Key-words:* Natural resource management, deer, GIS, participation, habitat use,
17 shelter, range use, local knowledge.

18 Correspondence: R. J. Irvine, Macaulay Institute, Craigiebuckler, Aberdeen, AB15
19 8QH, UK (Fax: +44 1224 311 556; e-mail: j.irvine@macaulay.ac.uk).

20 Word count: 7050

1 **Introduction**

2 Wildlife-habitat modelling can be used to bring together the knowledge needed to
3 effectively manage natural resources (Folke et al, 2005). For this, however, it must be
4 able to integrate the various sources of knowledge available about a system. This
5 paper describes the first step in the development of such a system for wild deer, in
6 which the knowledge that is found in the scientific realm is integrated with the
7 underutilised wealth of knowledge held by those who manage this species.

8 One of the aims of wildlife-habitat modelling is to enhance understanding of the
9 factors and mechanisms that bring about observed distribution patterns and to predict
10 changes in such distributions due to environmental or management change. The
11 usefulness of this depends crucially on identifying the key factors and mechanisms.

12 The inclusion of managers' knowledge can greatly contribute to this by linking animal
13 distribution patterns to land use and management (Johnson, Seip & Boyce, 2004;
14 Calheiros, Seidl & Ferreira, 2000). In the end, those affected by a decision should
15 participate in the decision making process (Nyerges, Jankowski & Drew, 2002) not
16 least because of the insights they may be able to bring regarding the underlying
17 mechanisms.

18 Participatory approaches have been used to identify, compare and integrate
19 practitioner and scientific knowledge (Bacic, Rossiter, & Bregt, 2006). Where spatial
20 information is relevant, as is likely to be the case for many natural resources, the
21 application of Participatory Geographical Information System (PGIS) has been shown
22 to facilitate communication, mediation and negotiation between stakeholders to
23 address management conflicts (Sandström et al, 2003). It is a means to visualise,
24 collate and analyse information from different sources so that, for example, manager
25 knowledge can be presented and discussed on more or less equal terms with scientific

1 data (Fedra, 1995; Janssen, Goosen & Omtzigt, 2006). Maps produced by integrating
2 such wider sources of data are more likely to be acceptable to stakeholders and can
3 thus form the basis for negotiation on the rights and responsibilities for managing a
4 shared natural resource.

5 We investigated the value of an ecologically-based GIS model in predicting red deer
6 (*Cervus elaphus* L) distribution in the Scottish Uplands. Here, red deer range freely
7 over areas larger than most individual land-holdings and provide income through
8 hunting, harvesting and tourism (PACEC, 2006) as well as imposing environmental,
9 economic and social costs through their grazing and trampling impacts (Gill, 1992;
10 Albon et al, 2007) and involvement in road traffic accidents (Langbein & Putman,
11 2005). The increasing conflict over deer management is largely due to three factors.
12 First, deer populations have increased (Clutton-Brock, Coulson & Milner, 2004).
13 Second, new legislation designed to protect the natural heritage has emerged (e.g.
14 Natura 2000 legislation; Irvine et al., 2008). Third, there has been a rise in the amount
15 of land owned by government agencies and non-governmental organisations which
16 aim to manage deer at low densities to reduce grazing impacts. This is in contrast with
17 general practices on sporting estates which tend to maintain populations at relatively
18 high densities to provide a hunting resource. This diversity of management objectives
19 can lead to conflict because of concerns that deer move from landownership units
20 with high deer densities to estates with lower deer densities.

21 Current predictions of deer distribution and impact only consider ecological aspects
22 and also tend to operate at a relatively large spatial scale (Albon et al., 2007; Brewer
23 et al, 2006; Ward et al, 2005), whereas management decisions are generally made at
24 the scale of ownership. A better representation of the management system at the
25 landscape level has the potential to move debate over deer management from one

1 based on general trends in population change or perceptions of failure to keep up with
2 an increase in deer numbers to arguments based on shared knowledge and
3 understanding of the resource, allowing for the establishment of an adaptive
4 management cycle (Folke et al. 2005).

5 We determined whether incorporation of managers' knowledge increases our ability
6 to predict deer distribution. For two areas of Scotland, we applied a GIS model based
7 on spatial environmental data and scientific ecological knowledge of deer habitat use
8 to predict deer distribution across a heterogeneous landscape. The model predictions
9 were evaluated by deer managers and compared with existing deer counts. The model
10 was then modified to incorporate managers' ecological knowledge of deer use of the
11 landscape. New predictions were evaluated against existing deer distribution data. We
12 discuss the extent to which this approach is successful in building a common pool of
13 knowledge that can facilitate the establishment of an inclusive adaptive management
14 system.

15

16 **Methods**

17 CASE STUDY AREAS

18 We used two case study areas based on Deer Management Groups (DMGs) selected
19 for variation in land ownership and associated management objectives (see Figure S1
20 in Supporting Information). DMGs comprise a group of land management units
21 (estates) over which a deer population can range (Nolan et al, 2003). Balquider DMG
22 (BDMG: 44,012ha) in Central Scotland comprises ten estates and land cover is 20%
23 woodland, 11% heather moorland and 41% grassland. West Sutherland DMG
24 (WSDMG: 149,892ha) comprises nine estates in North West Scotland and has 6%
25 woodland, 43% heather moorland and 31% grassland.

1

2 GIS-BASED HABITAT SUITABILITY MODEL

3 An existing GIS model (O'Brien, 2004) was used to generate a range suitability map
4 for red deer across the two DMGs. Individual GIS layers were calculated to give
5 forage preference, shelter preference, comfort (absence of biting flies) and human
6 disturbance for each pixel (50×50m). An overall suitability value was calculated for
7 each pixel by multiplying values across all layers.

8 To calculate forage preference values, each pixel was allocated to one of 14
9 vegetation types derived from the LCS88 dataset (MLURI 1988). The relative forage
10 preference for each of these was derived from the median of rankings provided
11 independently by seven grazing ecologists and separately for hinds and stags in
12 summer and winter. These linear rankings (1-14) were normalised to provide a scale
13 between zero and one.

14 Shelter preferences were generated by combining habitat shelter (offered by the
15 vegetation at that point) and terrain shelter (offered by the topography of the
16 surrounding landscape). Habitat shelter preference was assigned a value of one to
17 pixels with woodland and zero for all other vegetation types. The terrain shelter map
18 was calculated from the Digital Elevation Model (OS, 2003) to generate a
19 Topographic Exposure score (TOPEX - Wilson, 1994; Hannah, Palutikof & Quine
20 1995) normalised to vary between zero and one. This is essentially a measure of
21 shelter from wind offered by the local topography, where a higher score indicates less
22 exposure. Overall shelter preference was calculated by adding up habitat and terrain
23 shelter scores and capping the maximum value to one (woodland).

24 The comfort element represented the absence of biting flies (Blaxter et al., 1974) due
25 to windy locations in summer and was calculated as the complement of the shelter

1 map ($comfort_value = 1 - shelter_value$). Thus areas of high shelter were considered to
2 have low comfort in summer due to the likely presence of biting flies and vice versa.
3 The disturbance map was created by defining disturbance zones around paths (set to
4 100m, A. Sibbald, unpublished data). This disturbance map was modified to take into
5 account protection from disturbance offered by the vegetation by multiplying by the
6 inverse of the habitat shelter map described above. Finally, we generated deer range
7 suitability maps separately for stags and hinds and for winter (November-March) and
8 summer (April-July). The predicted map for stags in winter was evaluated by the
9 interviewed deer managers (see *Evaluation 1* below) and all four maps were
10 compared against deer count data (see *Evaluation 4* below).

11

12 MANAGERS' KNOWLEDGE OF DEER DISTRIBUTION

13 Practitioners' knowledge of deer use and movement across the landscape was
14 explored using map-based individual interviews. The twelve deer managers
15 interviewed in BDMG and eleven in WSDMG were responsible for the management
16 of 74% (32,548 ha) and 67% (10,1374 ha) of land respectively and provided a
17 contiguous and representative sample of the variation in management objectives
18 present in each DMG (see Fig S1). Interviewees were responsible for both setting
19 management objectives and practical deer management on their estates. For this
20 reason, on two occasions the interview was conducted with two individuals (manager
21 and stalker).

22 The interviewees were first asked to identify their estate's land use and deer
23 management objectives by referring to an A1-sized map (approximately 1:25,000) of
24 their area generated using ArcMap (v9.1, ESRI) with OS *Mastermap* as a base-layer.
25 Second, interviewees described deer range-use and distribution on their estates and

1 annotated the map to visually depict the geographical extent of hind and stag areas
2 (hind ground (hefts) and stag wintering ground), directions of deer movement, feeding
3 sites, fencing and disturbance from recreational use of footpaths. Factors determining
4 stag and hind locations and movements were then discussed. Finally, each interviewee
5 was invited to evaluate the GIS model predictions of deer habitat suitability on their
6 estate for stags in winter (*Evaluation 1*). For simplicity, the evaluation map only
7 highlighted the top 25% of pixels predicted to be the most suitable for deer and
8 interviewees were asked to comment on whether predictions were “good”, “bad” or
9 “fair” and to motivate their evaluation.

10 The annotated maps were then digitised in ArcMap including fences and roads as line
11 structures, and hind and stag ground as polygons.

12

13 EVALUATIONS OF THE MODELS

14 *Evaluation 1 - Managers' knowledge of deer distribution.*

15 The interview recordings were transcribed and text analysis (Ryan and Bernard, 2000)
16 was used to summarize the interviewees' understanding of the interconnection
17 between deer behaviour and biophysical factors. First, transcripts were coded based
18 on the biophysical factors mentioned and whether these were perceived to influence
19 deer positively (i.e. increasing the likelihood of deer use), negative or
20 neutral/uncertain (when interviewees were unsure or did not specify this effect).

21 These factors were coded separately for hinds and stags for each interviewee and
22 summarised at the DMG level (see Table S21). Second, the codes were then re-
23 classified to categories directly comparable to the GIS layers (Table 1) and this
24 formed the basis for modifying the GIS with manager knowledge. Whilst the total
25 number of mentions for a factor may be an indication of its importance, it may also be

1 affected by the extent to which that factor is present in the area discussed, or
2 influenced by interview length and personality of the interviewee. Therefore, the
3 relative number of mentions of a factor was converted into a relative weighting for
4 use in modifying the GIS.

5

6 *Evaluation 2 - Pixel analysis of hind and stag polygons*

7 Using the zonal stats function in ArcMAP we extracted the mean values for the
8 topographical (slope/altitude), shelter (TOPEX) and habitat (vegetation type) elements
9 in 36 polygons in BDMG (27 hind, 11 stag) and 81 in WSDMG (55 hind, 32 stag).
10 We then used the Hawth's Tools extension (Beyer, 2004) for ArcMap to randomly re-
11 distribute polygons across the DMGs 1000 times and extract the mean values for these
12 same elements. The distribution of these means were depicted as box-plots and
13 represent the background distribution, or range of values as expected by chance.
14 These were compared with the mean values in the stags and hind manager-derived
15 polygons.

16

17 *Evaluation 3 – Comparing manager-derived hind and stag polygons with deer counts*

18 Although count data exist for the whole of both DMGs, they are one-off counts which
19 are difficult to interpret (Daniels et al., 2006; Mysterud et al, 2007). Therefore we
20 preferred to carry out evaluations using a smaller area (Estate Glen Feshie (GF) in
21 BDMG, see Fig S1b) for which spatially explicit, monthly, geo-referenced red deer
22 point counts (July 2004 to May 2007) were available. Using these data, we
23 determined the proportion of both groups and total numbers of hinds and stags
24 counted that were within the manager derived hind and stag polygons. These data

1 were then compared to predictions based on the proportions counted in randomly
2 distributed polygons.

3

4 *Evaluation 4 - Validating GIS predictions against deer count data*

5 The GIS model predictions were validated against point count data from Estate GF
6 aggregated by sex and season. To determine the goodness-of-fit of the four GIS
7 prediction maps (summer hinds, summer stags, winter hinds and winter stags) three
8 zones were defined: i) zero scores, for example, fenced areas, where the GIS excluded
9 deer; ii) low scores, containing half of the remaining pixels with the lowest prediction
10 scores; and iii) high scores, containing the remaining pixels with the highest
11 prediction scores. The percentage of the aggregated point counts that fell in each of
12 above zones was calculated (Model 0).

13 The GIS used in 'Model 0' was modified by a) adding data derived from the manager-
14 annotated maps relating to man-made physical features such as paths and fences, and
15 b) adjusting the relative importance of the main GIS layers to reflect their qualitative
16 importance as derived from the interviews. For each step-wise change in the model,
17 the percentage increase in the number of counted groups/individuals that were in areas
18 with the highest prediction scores was calculated. In 'Model 1' the GIS was modified
19 by including changes to the weighting for 'terrain shelter' to reflect the interview
20 analysis. This was done by scaling TOPEX scores relative to the theoretical minimum
21 and maximum values ($\text{terrain shelter} = (\text{TOPEX}/1440)+0.5$); in practice, this meant
22 that scores no longer ranged from 0 to 1 but from 0.4 to 0.8, thus reducing the effect
23 of terrain shelter. For 'Model 2' a new disturbance map was created by including an
24 updated path map. For 'Model 3' the modified comfort layer was added where the
25 effect of flies was removed (since this was not mentioned by interviewees) and slope

1 and altitude effects added (which were mentioned). The slope preference component
2 of the comfort map was set to 1 for all slopes with angles <30° and scaled linearly
3 from 1 to 0 those between 30° and 90°. To capture managers' observations the
4 elevation component was set to produce a slight preference for areas around 400m in
5 winter up and 600m in summer. For 'Model 4' the habitat shelter layer was modified
6 to reflect the importance of this factor by allowing more categories to have an
7 influence so that the value of 1.0 was assigned to dense woodland, 0.5 for open
8 woodland, 0.3 for scrub, 0.2 for heather moorland, 0.1 for bracken and 0 for all other
9 vegetation types. For 'Model 5' we added the effect of the prevailing (NW) wind in
10 winter. Finally, 'Model 6' altered the way the four GIS layers were integrated. For
11 this it was necessary to re-scale the range of scores within each characteristic in a non-
12 linear manner since a linear scaling would multiply all preference scores by a constant
13 value and thus give the same output. Therefore, we used power functions like
14 $Preference\ score = shelter^a \times forage^b \times comfort^c \times (1 - disturbance^d)$
15 where the exponents, a , b , c and d (set to one in Model 0) can be chosen to reflect the
16 emphasis put on each characteristic. Since each layer has values in the range 0 to 1,
17 any exponent will leave the resulting values in the same range ($0^a = 0$ and $1^a = 1$), but
18 rescaled non-linearly.

19

20 **Results**

21 *Evaluation 1 - Managers' knowledge of deer distribution*

22 Within the estates that the interviewed deer managers represented (see Fig S2), the
23 managers commented on 78 locations that the GIS predicted as highly suitable for
24 deer across the two DMGs. Of these 31 areas were identified as areas well used by

1 deer and 16 as being partially used. Thus, there appears to be considerable scope for
2 improving our local predictions of deer distribution.

3 The interview transcripts were analysed to provide insights on how model predictions
4 could be improved using local knowledge. Five main factors affecting deer
5 distribution emerged (see Table S2): shelter (213 mentions), topography (139),
6 feeding (127), weather (137) and disturbance (97). Shelter was identified by 17 out of
7 18 estates as positively determining the presence of deer in a particular location with
8 nearly twice as many mentions as any other factor (120 and 93 for stags and hinds
9 respectively). The topographic characteristics of the landscape were the second most
10 mentioned element for stags and third most mentioned for hinds (87 and 52
11 respectively). Whilst shelter generally represented an attractive element for deer,
12 topography was recognised to also have negative attributes. The suitability of an area
13 to provide feeding was the third most mentioned element for both stags and hinds.
14 Weather and disturbance were mentioned least.

15 Table 1 illustrates the frequency of mentions of the above factors recoded to directly
16 categorise them into the main elements used in the GIS. This, together with the
17 context in which these factors were mentioned formed the basis for justifying how the
18 GIS was modified with manager knowledge. Results indicate subtle variation between
19 sexes and DMGs in the relative frequency of these main factors but in general, shelter
20 comfort (i.e. slope and elevation), forage and disturbance were mentioned in an
21 approximate ratio of 4:2:2:1 (see Table 1 overall totals).

22

23 *Evaluation 2 - Pixel analysis of the hind and stag polygons*

24 To evaluate the managers' general standpoint that physical factors such as shelter and
25 topography are more influential to deer distribution than forage availability, the bio-

1 physical characteristics of the manager-derived hind and stag polygons were
2 compared with the background variation calculated from randomly placed sets of
3 polygons.

4 Both altitude and slope were found to underlie the distribution of deer across the
5 landscape (Fig. 1). In BDMG, where ground was steeper, hinds and stags were found
6 on similar slopes to that generally found in the area whereas in WSDMG where slopes
7 are generally low, animals were found on steeper ground than expected when
8 compared to the random distribution (Fig 1a). However, for altitude, both hinds and
9 stags were found on higher ground than would be expected by chance in both DMGs
10 (Fig. 1b). Generally, WSDMG was of higher altitude and had steeper ground than
11 BDMG, illustrating the need to take into account differences in landscape
12 characteristics between areas when interpreting factors underlying deer distribution.

13 That physical landscape differences between sites may indeed lead to differential deer
14 use became evident from inspecting terrain shelter using TOPEX scores (Fig. 2).
15 Here, hind and stag polygons in the generally more exposed WSDMG (i.e. higher
16 TOPEX scores) had a more sheltered character than expected by chance, notably for
17 grounds with southerly and easterly aspect components.

18 Yet, there was little evidence for deer preferentially using sheltered areas in the
19 generally more sheltered BDMG. Analysis of the aspect characteristics of the
20 manager and random polygons supports this result (see Fig S2).

21 In contrast, comparison of the manager-derived polygons with the proportion of each
22 vegetation type expected by chance (Fig 3) revealed little evidence for strong
23 preferences. It showed that proportions in each were similar except that hind and stag
24 polygons in BDMG appeared to have more smooth grass and less plantation
25 woodland than expected by chance. However, the main reason for DMG differences

1 in the proportions of vegetation types underlying deer polygons were differences in
2 habitat proportions between the two areas.

3 In conclusion, areas used by deer, as identified by managers, differ from background
4 regarding physical landscape features with stags seeking more sheltered, less steep
5 and lower altitude areas than hinds but there is little evidence that these areas differ
6 from background in their vegetation characteristics.

7

8 *Evaluation 3 – Comparing manager-derived hind and stag polygons with deer counts*

9 We evaluated how well the locations (points) of counted deer in Estate GF matched
10 with manager derived stag and hind polygons. The proportion of the number of point
11 counts and sum of animals at those points that lay inside the manager-derived
12 polygons indicated that for hinds there were about 2.7 and stags about 1.6 times as
13 many point counts inside polygons than would be expected by chance (Table 2 and
14 Fig 4c) and d)). This indicates that managers can make reasonable predictions of deer
15 distribution at the local scale.

16

17 *Evaluation 4 - Validating GIS predictions against deer count data*

18 Figure 4a shows the count data distributed across Estate GF. The estate is subdivided
19 into areas where pixels are characterised as being either in the top or bottom half of
20 preference values as predicted by 'Model 0' (original model). The effect of the five
21 modifications to the GIS model (Models 1-6) derived from the interview analysis on
22 the spatial fit with the count data is outlined in Table 4. Model 1 incorporated reduced
23 terrain shelter importance by reducing the TOPEX score weighting and increased the
24 fit of the prediction to count data by on average 17%. The addition of a modified
25 fence layer (Model 2) didn't improve the prediction but a modified disturbance layer

1 (by adding an updated paths layer – Model 3); a modified habitat shelter layer (Model
2 4) and a modified comfort layer (including the interview derived effects of slope and
3 elevation - Model 5) increased the fit by a further 7%, 6% and 4% respectively. For
4 Model 6 the factors affecting of deer distribution (shelter, forage, comfort and
5 disturbance) were allocated the exponents 0.5, 1, 1 and 2 to reflect their relative
6 importance (4:2:2:1) in Table 1. This had a small 1.4% improvement compared to
7 Model 5. As a whole, the modifications improved the fit of the suitability map
8 predicted by the GIS to the count data from average 45% (range 25-56%) to around
9 80% (73-85%) with the biggest increase for stags and hinds in summer. The weakest
10 effect was for stags in winter but even here the increase in fit was around 25%. Fig 4b
11 shows the map of deer counts overlaid on the GIS predictions for Model 6 showing
12 that point count location salmost entirely reside in areas predicted to be highly
13 suitable for deer. Comparison with 4c) and d) show that although managers know
14 where some deer are, there are areas where deer are counted but not recognised as
15 core areas by managers yet these counts match with the GIS predictions. This
16 demonstrates that a superior understanding of deer distribution at the landscape scale
17 can be gained by combining local and scientific knowledge.

18

19 **Discussion.**

20 Integrating knowledge from deer managers with scientific knowledge on red deer
21 ecology significantly improved the ability of a GIS based model to predict deer
22 distributions. This has important implications for the management of a natural
23 resource such as deer. First, this represents a new method to get better predictions of
24 deer distribution without having to resort to expensive and time consuming counting
25 methods (Morellet et al.,2007; Willebrand, Sandström & Lundgren, 2006).

1 Second, by incorporating local knowledge on management and environmental factors,
2 the predictions are more likely to be accepted by local deer managers and the model
3 can then be used support adaptive management, facilitating negotiation and building
4 consensus among diverse stakeholders.

5 *Using local knowledge to determine deer distribution.*

6 Whilst a simple ecologically based GIS was only able to predict deer distribution with
7 around a 50% match to both manger knowledge and detailed count data, the modified
8 model improved the fit to count locations to around 80% and with greater precision
9 (Fig 4a versus b). Although managers were good at identifying areas where deer are
10 located (Table 2) comparison of fig 4c and d with fig 4b) show that deer are also
11 found outside the manager defined areas but these were predicted better by the
12 modified GIS. Because of the problems with count data (Daniels et al., 2006;
13 Mysterud et al, 2007), using a GIS where the interaction between key factors is
14 determined from deer manager knowledge is justifiable on the basis of our results.

15 Whilst there where no surprises in the factors that managers identified as being
16 important, their relative importance has not previously been quantified and
17 incorporating this had a significant impact on model predictions. Two types of local
18 knowledge were important in improving the model predictions: First, we added
19 information on local physical characteristics such as fences, paths, tracks which is
20 largely unavailable except from local managers. Second, the rules determining the
21 relative importance of the main elements in the GIS were allowed to be modified by
22 stakeholder knowledge of the environmental cues that deer respond to. Notably, both
23 our evaluations of the local knowledge indicated that ‘habitat shelter’ was more
24 influential than forage value of habitats and the addition of a modified terrain shelter
25 layer had a particularly large effect. The final modification was to use power terms to

1 alter the scale of the four core elements of the GIS. This gave little advantage over the
2 earlier changes to the model (models 1-5,) possibly because the earlier modifications
3 had the indirect effect of changing the relative weightings between the elements. One
4 of the important considerations when interpreting local knowledge is the need to
5 understand the biophysical composition of the area over which this knowledge has
6 been developed. The analysis of the hind and stag polygons suggested differences
7 between DMGs in characteristics of the hind and stag polygons but only when this
8 data is compared to background distributions could these differences be ascribed to
9 underlying bio-physical differences between the two DMGs rather than differences in
10 the deer preferences between the two areas.

11 *Building consensus.*

12 Natural resources are subject to increasing demands and exploitation. They are
13 affected by governmental regulation, international agreements, market mechanisms,
14 cultural traditions and individual preferences. The use of regulatory powers to achieve
15 public objectives for natural resource management on private land is often limited and
16 expensive and can lead to conflict, creating barriers to dialogue between private and
17 public interests. In addition, management of natural heritage in the wider countryside
18 is potentially thwarted because there is not enough data and information on the spatial
19 extent of species, and their impacts .An alternative to regulation is to adopt a
20 collaborative approach in order to achieve public objectives (Janssen et al, 2006).

21 Whereas GIS is traditionally used to enforce top-down expert analysis with the
22 information used and agenda set by outside agencies rather than local managers, PGIS
23 offers a means to promote collaboration, transparency and trust by incorporating
24 multiple sources of information including that derived from local experts (Cinderby,
25 1999; Lenz & Peters, 2006; McCall and Minang 2005; Johnson et al, 2004) and is

1 therefore more likely to lead to new management solutions that are acceptable to all
2 stakeholders because it puts local managers on a more even footing with government
3 and promotes bottom-up policy development (Calheiros, Seidl & Ferreira, 2000). In
4 addition, this tool can provide stakeholders with insights the effect of alternative
5 management scenarios and environmental change. For example, when this type of
6 approach was used to address a conflict over water pollution at a watershed level,
7 spatial information was shown to improve communication between the information
8 generators and the other stakeholders leading to increased understanding, consensus
9 and new, more appropriate solutions (Bacic et al, 2006). Despite the simplistic nature
10 of our GIS, researchers and agencies need to be aware that the shared knowledge is
11 effectively only available to those with GIS skills (although paper outputs of the
12 digital system can be annotated to capture new elements or changes in existing spatial
13 data). For example, in our study, the importance of co-existing sheep and the effect of
14 rainfall were also discussed by managers but data on these factors are currently not
15 available at the appropriate resolution.

16

17 As policy makers move from focussing management of a particular habitat or species
18 towards landscape scale management (JNCC, 2007), decisions become more complex
19 and need to take into account the biological, physical and socio-political drivers
20 affecting the resource and how they interact with the local managers (Sandström et al,
21 2003). In our study, mapping was carried out at the scale of the deer range use. This is
22 important to its value in facilitating discussion and negotiation between land managers
23 over whose boundaries the deer range freely. A similar approach is being used to help
24 resolve forest management conflicts in Sweden where woodland is both a resource for
25 timber production and an important wintering ground for semi-domestic reindeer

1 because of the forest lichens. In this system, mapping has facilitated a consensus on
2 management actions that both protect lichen and allow timber production (Sandström
3 et al, 2006). Our approach has demonstrated that a simple model of deer distribution
4 based on spatial data sets can be improved for local purposes by capturing local
5 knowledge on physical features and drivers of deer distribution. In addition, the work
6 demonstrates that using maps to capture the spatial knowledge of managers is
7 appropriate to the management of a mobile natural resource, distributed across a
8 landscape that is heterogeneous in terms of topography, habitat, ownership and
9 management objectives. This recognises that management issues are locally specific
10 but need a landscape scale approach. PGIS provides a means to take generic
11 ecological models and give them local applicability (Lenz and Peters, 2006).

12 **Acknowledgements.**

13 The research was funded by RELU (RES 227-025-0014) with further support by
14 Defra, Scottish Executive and Forestry Commission. Thanks to all the managers in the
15 two case study areas. In memory of Peter Kirk (Deer Commission for Scotland).

16

17 **References**

- 18 Albon, S.D., Brewer, M.J., Nolan, A.J., Cope, D. (2007) Quantifying the grazing
19 impacts associated with different herbivores on rangelands. *Journal of Applied*
20 *Ecology*, **44**, 1176-1187.
- 21 Bacic, I.L.Z. Rossiter, D. G., & Bregt, A. K. (2006) Using spatial information to
22 improve collective understanding of shared environmental problems at watershed
23 level. *Landscape and Urban Planning*, **77**, 54–66.
- 24 Beyer, H.L. (2004) Hawth's Analysis Tools for ArcGIS. Available at
25 <http://www.spataleecology.com/htools>.
- 26 Blaxter, K.L., Kay, R.N.B., Sharman, G.A.M., Cunningham, J.M.M., Hamilton, W.J.
27 (1974) Farming the red deer. The first Report of Investigations by the Rowett Institute
28 and the Hill Farming Research Organisation. Edinburgh: Her Majesty's Stationary
29 Office.
- 30 Brewer, M.J., Elston, D.E., Hodgson, M.E.A., Stolte, A.M., Nolan, A.J. & Henderson,
31 D.J.A (2004) A spatial model with ordinal responses for grazing impact data.
32 *Statistical Modelling*, **4**, 127-143.

- 1 Calheiros, D. F., Seidl, A. F. & Ferreira, C. J. A. (2000) Participatory research
 2 methods in environmental science: local and scientific knowledge of a limnological
 3 phenomenon in the Pantanal wetland of Brazil. pp. 684-696.
- 4 Cinderby, S. (1999) Geographic information systems (GIS) for participation: the
 5 future of environmental GIS? *International Journal of Environment and Pollution*, **11**,
 6 304-315.
- 7 Clutton-Brock TH, Coulson T, Milner JM. (2004) Red deer stocks in the Highlands of
 8 Scotland. *Nature*, **429**, 261-262.
- 9 Daniels M.J. 2006. Estimating red deer (*Cervus elaphus*) populations: an analysis of
 10 variation and cost-effectiveness of counting methods. *Mammal Review* 36, 235-247 .
- 11 Fedra, K. (1995) Decision support for natural resources management: models, GIS,
 12 and expert systems. *AI Applications*, **9**, 3-19.
- 13 Folke, C., T. Hahn, P. Olsson and J. Norberg (2005) Adaptive governance of social-
 14 ecological systems. *Annual Review of Environment and Resources*. 30: 441-473.
- 15 Gill, R.M.A. (1992) A review of damage by mammals in North temperate forests: 1.
 16 Deer. *Forestry*, **65**, 145–169.
- 17 Hannah, P., J.P. Palutikof and C.P. Quine. (1995) Predicting windspeeds for forest
 18 areas in complex terrain. In *Wind and Trees*. M. P. Coutts and J. Grace (eds.).
 19 Cambridge University Press. Cambridge. pp. 113-129.
- 20 Janssen, M.A., Goosen, H & Omtzigt, N. (2006) A simple mediation and negotiation
 21 support tool for water management in the Netherlands. *Landscape and Urban*
 22 *Planning*, **78**, 71–84.
- 23 Johnson, C.J., Seip, D.R. & Boyce, M.S. (2004) A quantitative approach to
 24 conservation planning: using resource selection functions to map the distribution of
 25 mountain caribou at multiple spatial scales. *Journal of Applied Ecology*, **41**, 238–251.
- 26 Joint Nature Conservation Committee. (2007) UK Biodiversity Action Plan
 27 <http://www.ukbap.org.uk/default.aspx>. Accessed 28-07-2008.
- 28 Langbein, J. & Putman, R.J. (2006) National Deer-Vehicle Collisions Project
 29 Scotland (2003-2005). The Deer Initiative, Wrexham, UK.
 30 <http://www.deercollisions.co.uk/> Accessed 28-07-2008.
- 31 Lenz, R. & Peters, D. (2006) From Data to Decisions: Steps to an application oriented
 32 landscape research. *Ecological Indicators*, **6**, 250-263.
- 33 Mastermap, Pan-Government agreement v1.0, 2003. Ordnance Survey © Crown
 34 copyright 2008
- 35 McCall M.K. & Minang P.A. (2005) Assessing participatory GIS for community-
 36 based natural resource management: claiming community forests in Cameroon. *The*
 37 *Geographical Journal*, **171**, 340–356
- 38 MLURI. (1992) Land Cover of Scotland 1988. Digital Dataset Release 2, 1:25,000.
 39 The Macaulay Land Use Research Institute, Aberdeen
- 40 Morellet, N., Gaillard, J.-M., Hewison, A. J. M., Ballon, P., Boscardin, Y., Duncan,
 41 P., Klein, F., Ois & Maillard, D. (2007) *Indicators of ecological change: new tools for*
 42 *managing populations of large herbivores*. *Journal of Applied Ecology*, **44**, 634-643
- 43 Mysterud A, Meisingset EL, Veiberg V, Langvatn R, Solberg EJ, Loe, L.E. &
 44 Stenseth, N.C. (2007) Monitoring Population Size of Red Deer *Cervus Elaphus*: An
 45 Evaluation of Two Types of Census Data from Norway. *Wildlife Biology*, **13**, 285–
 46 298.
- 47 Nolan, A.J., Henderson, D.J., Stolte, A.M., Hope, I.M. and Scott, R. (2003)
 48 Assessment of grazing and trampling impacts on rangeland for management planning

1 by land managers and government agencies in Scotland, UK. *African Journal of*
2 *Range & Forest Science*, **20**, 123-124.

3 Nyerges T., Jankowski P., Drew C. (2002) Data-gathering strategies for social-
4 behavioural research about participatory geographical information system use.
5 *International Journal of Geographical Information Science*, **16**, 1-22.

6 O'Brien, S. (2005) Development of a decision support tool (WoodDeer) to aid the
7 management of deer in woodlands in the uplands of Scotland. P8/B (304772)

8 OS, (2003) Land-Form PROFILE ® Digital Terrain Model, 1:10,000 Raster.
9 Ordnance Survey, Southampton

10 PACEC. (2006) The Economic and Environmental Impact of Sporting Shooting. A
11 report prepared by PACEC on behalf of BASC, CA, and CLA and in association with
12 GCT. PACEC 49-53 Regent Street Cambridge CB2 1AB

13 Ryan, G. W. & Bernard, H. R. (2000) Data management and analysis methods. (In
14 Handbook of qualitative research, eds N.K. Denzin & Y.S. Lincoln). Sage
15 publications inc., London, 769-802

16 Sandström, C., Moen, J., Widmark, C., Danell, Ö. (2006) Progressing toward co-
17 management through collaborative learning: forestry and reindeer husbandry in
18 dialogue. *The International Journal of Biodiversity Science and Management*, **2**, 326-
19 333.

20 Sandström, P., Pahlen, T.G., Edenius, L., Tommervik, H., Hagner, O., Hemberg, L.,
21 Olsson, H., Baer, K., Stenlund, T., Brandt, L.G., Egberth, M. (2003) Conflict
22 Resolution by Participatory Management: Remote Sensing and GIS as Tools for
23 Communicating Land-use Needs for Reindeer Herding in Northern Sweden. *Ambio*,
24 **32**, 557-567.

25 Ward, A. I. (2005) Expanding ranges of wild and feral deer in Great Britain. *Mammal*
26 *Review*, **35**, 165-173.

27 Willebrand, T., Sandström, C. & Lundgren, T. (2006) Reaching for new perspectives
28 on socio-ecological systems: exploring the possibilities for adaptive co-management
29 in the Swedish mountain region. *The International Journal of Biodiversity Science*
30 *and Management*, **2**, 359-369.

31 Wilson, J.D., 1984. Determining a TOPEX score. *Scottish Forestry*. **38**, No. 4, 251 -
32 256

33
34 Supporting Information

35 Additional Supporting Information may be found in the online version of this article:

36 Table S1. Interview transcript analysis.

37 Fig. S1. Deer Management Group case study areas.

38 Fig. S2. Aspect characteristics of areas used by deer.

39

1 Table 1. Number of mentions of factors (comparable with the elements used in the
2 GIS) affecting deer distribution derived from interview transcripts: + indicates that
3 deer are attracted by this type of factor and – means they tend to avoid areas because
4 of this factor. N/U indicates that this factor was not mentioned or the interviewee was
5 uncertain. n = the number of estates in the sample. These data are used to facilitate a
6 qualitative relative re-ranking of the element’s relative importance in the GIS
7 prediction.
8

Factor	Shelter		Forage		Comfort		Disturbance							
	Terrain	Habitat			Slope	Elevation	Walkers	Stalking						
	+	-	+	-	+	-	+	-						
Hinds														
BDMG (n=10)	6	0	31	0	20	0	3	0	12	0	2	4	0	0
WSDMG (n=8)	12	0	39	0	24	0	1	2	22	6	0	2	0	5
<i>Column total</i>	<i>18</i>	<i>0</i>	<i>70</i>	<i>0</i>	<i>44</i>	<i>0</i>	<i>4</i>	<i>2</i>	<i>34</i>	<i>6</i>	<i>2</i>	<i>6</i>	<i>0</i>	<i>5</i>
<i>Factor total</i>		<i>88</i>			<i>44</i>			<i>46</i>				<i>13</i>		
Stags in winter														
BDMGA (n=10)	15	0	57	1	24	1	2	0	23	8	0	3	1	7
WSDMG (n=8)	4	0	36	0	33	0	6	0	29	1	0	9	0	3
<i>Column total</i>	<i>19</i>	<i>0</i>	<i>93</i>	<i>1</i>	<i>57</i>	<i>1</i>	<i>8</i>	<i>0</i>	<i>52</i>	<i>9</i>	<i>0</i>	<i>12</i>	<i>1</i>	<i>10</i>
<i>Factor total</i>		<i>113</i>			<i>58</i>			<i>69</i>				<i>23</i>		
<i>Overall factor total</i>		<i>201</i>			<i>102</i>			<i>115</i>				<i>36</i>		

1 Table 2. The ratio of actual point locations and the sum of deer at those points lying
 2 inside manager polygons compared to what would be expected in randomly placed
 3 polygons (4th row). For the whole of Estate GF, the total count points (locations) and
 4 the sum of the deer at those points are shown (row 1) followed by the number of
 5 points and sum of animals in the manager polygons (row 2). The number of points
 6 and sum of deer expected in randomly placed equivalent polygons is indicated in row
 7 3. In row 4, a ratio of around 1:1 is expected if manager-derived polygons are no better
 8 at matching count data than random.

Feature:-	Number of points counted		Sum of deer in the points counted	
	Hinds	Stags	Hinds	Stags
1. Total within Estate GF	374	137	3619	1541
2. Total within polygons	182	37	1597	548
3. Total expected in polygons (from random)	67.7	23.3	655.6	262.0
4. Ratio of actual:expected	2.69	1.59	2.44	2.09

9

1 Table 3. The percentage of deer count points on Estate GF that fell within the 50% of
 2 pixels with high preference values for 6 different model runs corresponding to the
 3 various changes made to the GIS. Model 0 = original GIS predictions. Models 1-5 add
 4 sequentially the modified terrain shelter (down weighted effect of TOPEX score),
 5 fence and path layers, habitat shelter (the shelter component of habitat structure) and
 6 the comfort layer (slope and elevation preferences). Model 6 incorporates weightings
 7 from the use of power terms to modify the prediction calculation.

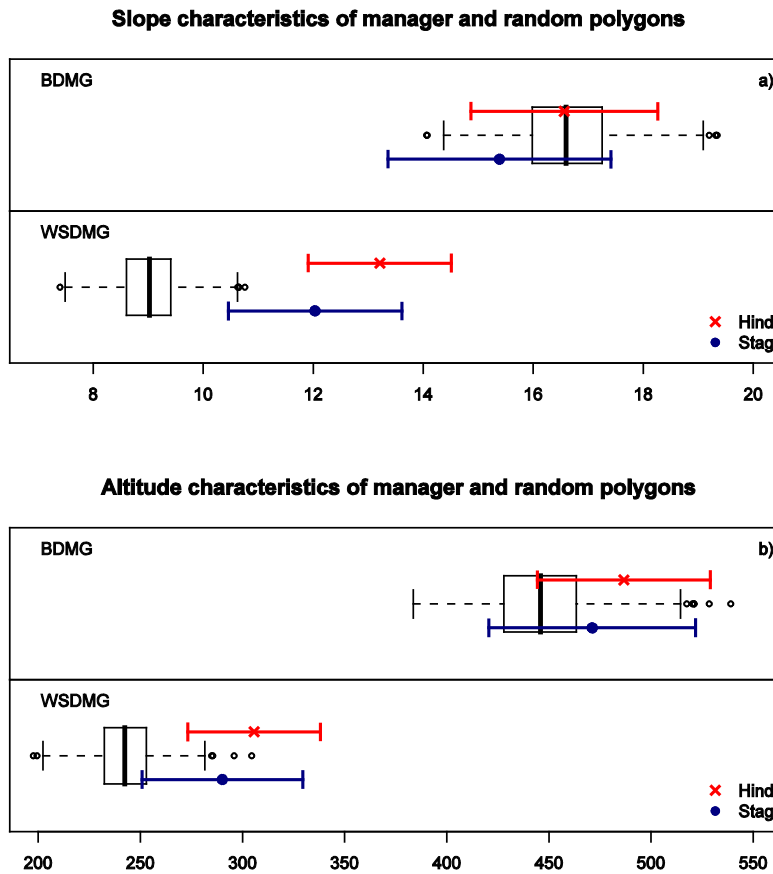
Prediction for:-	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Hinds in summer	48.1	62.8%	63.4%	69.7%	80.9%	85.2%	84.3%
Stags in summer	25.3	61.2%	58.3%	68.6%	75.0%	84.1%	83.0%
Hinds in winter	55.7	60.9%	60.5%	67.6%	75.0%	75.7%	79.7%
Stags in winter	51.1	63.8%	65.0%	70.8%	72.3%	73.0%	76.6%
Mean	45.1	62.2%	61.8%	69.2%	75.8%	79.5%	80.9%
Cumulative change		+17.1%	+16.7%	+24.1%	+30.7%	+34.4%	+35.8%
Step change		+17.1%	-0.4%	+7.0%	+5.9%	+3.7%	+1.4%

8

9

1 FIGURES

2 Figure 1



3

4 Figure 1. Box-plots describing the distribution of possible slopes (a) or altitudes (b) in

5 the landscapes of the two study areas (BDMG & WSDMG) along with mean and

6 confidence limits for the manager-derived polygons for hind hefts (light cross

7 symbol) and stag wintering grounds (dark solid symbol). If a mean is outside the

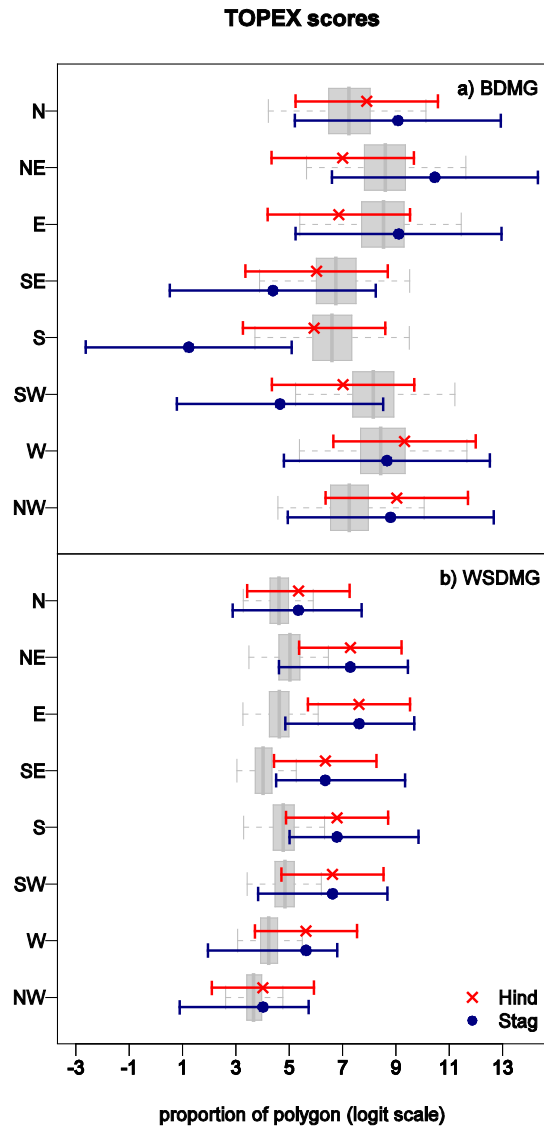
8 central white bar (depicting 25, 50 and 75% quartiles; whiskers enclose 95%

9 confidence intervals) the deer were described by the managers to utilise ground that

10 was on average either significantly higher or lower in slope or altitude than would be

11 expected by chance.

1 Figure 2

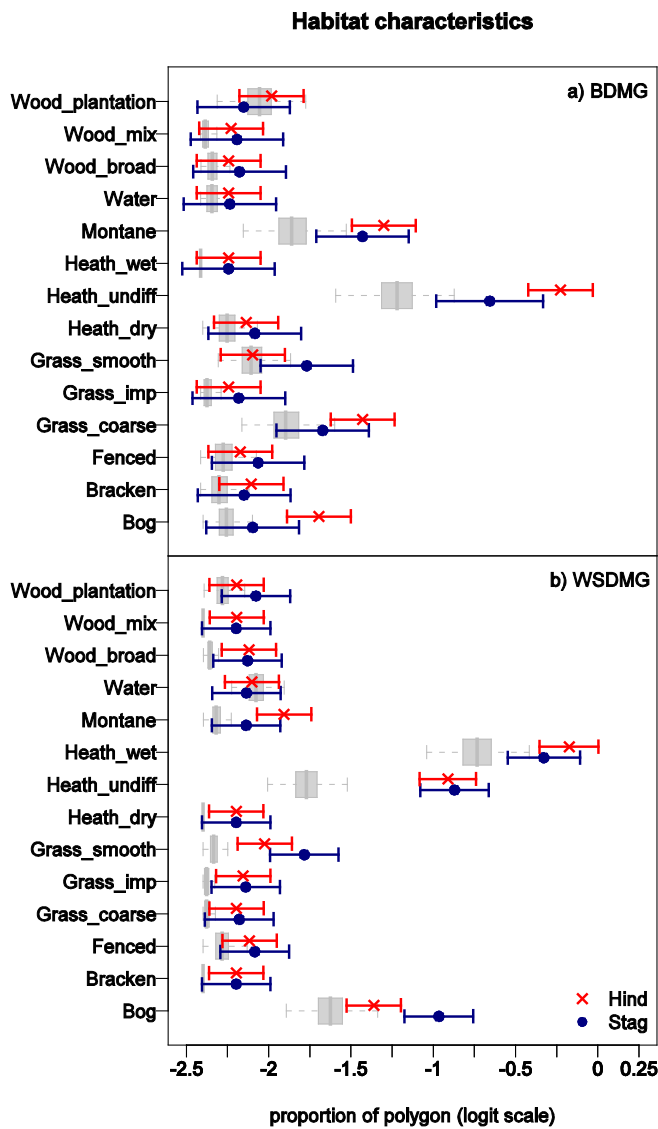


2

3 Figure 2 Box-plots of the background distribution of the TOPEX scores in each aspect
4 found in the BDMG and WSDMG areas. These are overlaid with the mean TOPEX
5 scores (plus confidence intervals) for the manager-derived polygons for hind hefts
6 (light cross symbol) and stag wintering grounds (dark solid symbol); a) represents the
7 values for BDMG and b) WSDMG. Separate mean TOPEX scores are calculated for
8 each of the 8 cardinal points of the compass

9

1 Figure 3



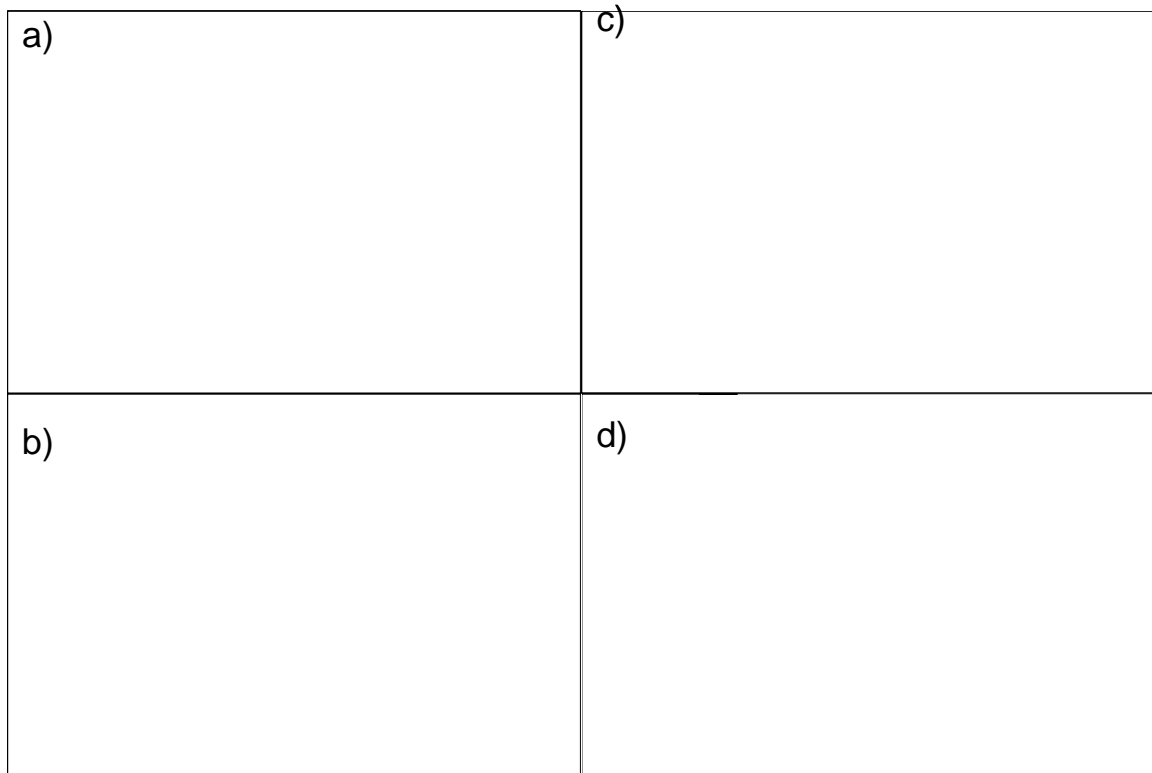
2

3 Figure 3 Box-plots of the background distribution of the proportion of each vegetation
4 type found in the BDMG and WSDMG areas. These are overlaid with the mean
5 proportion of each vegetation type (plus confidence intervals) for the manager-derived
6 polygons for hind hefts (light cross symbol) and stag wintering grounds (dark solid
7 symbol); a) represents the values for BDMG and b) WSDMG.

8

9

1 Figure 4.



2

3 Figure 6. Maps of Estate GF: a) shows the location of deer count data for stags in
4 winter superimposed on the original GIS predictions of deer suitability. Hatched
5 areas are the pixels predicted to have the highest suitability. white areas are predicted
6 to have low suitability or are fenced out;. b) as for a) but using the modified GIS
7 predictions from Model 6; c) shows the location of hind count data and the manager
8 derived hind polygons and d) show the same pattern for stag counts polygons.

9