iDeer: A decision-support tool for managing deer alongside woodland creation

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Abstract

Increasing deer (Cervidae) densities driven by land-use change and climate warming represent a growing challenge to the establishment and management of woodlands across temperate biomes. Targeting deer management is challenging without spatially explicit information on potential impact risks under alternative management scenarios. Here we present the iDeer Tool (https://ideer-project.shinyapps.io/ideer/), an interactive decision-support tool for predicting deer impact risk to woodlands across England and Wales. We present the Tool's underlying spatially explicit Bayesian Belief Network models. Through iterative expert elicitation, we co-developed influence diagram structures and conditional probability tables, then validated spatial predictions across multiple landscapes. The model structures incorporate landscape-scale influences on key ecological processes related to deer energy acquisition and loss, and associated habitat requirements for nutritional resources and shelter. The tool enables users to view current deer impact risk maps for large-bodied and small-bodied deer species and assess how different woodland establishment scenarios may alter the distribution of impact risk across landscapes, beyond the immediate planting sites. The tool facilitates pre-emptive, collaborative action among landowners by providing risk maps for integration into management plans and grant applications. Our replicable framework can be adapted to develop similar decision-support tools for different species, countries, and land-use management challenges.

Introduction

Increasing densities and expanding distributions of deer in Europe, driven by land-use change and the warming climate, pose growing challenges to human land-use objectives (Reimoser, 2003; Ward, 2005; Putman *et al.*, 2011; Croft *et al.*, 2019). While large herbivores are important for ecosystem function and resilience (Ripple *et al.*, 2015; Fløjgaard *et al.*, 2022), high densities can inhibit the natural regeneration of vegetation, simplify forest composition and structure, reduce forest resilience, and undermine the woodland creation efforts that are essential to tackling the climate and biodiversity emergencies (Gill and Beardall, 2001; Côté *et al.*, 2004; Ramirez, Jansen and Poorter, 2018). Coupling successful woodland creation schemes with effective deer management is essential to ensure successful tree establishment and growth.

Although measures such as culling and fencing are commonly used to reduce damage (Barton et al., 2022), they are costly and demanding (Aebischer, Wheatley and Rose, 2014; VerCauteren et al., 2010). In landscapes such as lowland Europe where ownership of land parcels is finely divided, there is reduced incentive for landowners to invest in mitigating deer impacts if neighbouring woodlands are unmanaged (Putman, Watson and Langbein, 2011). Deer move freely across property boundaries and respond to changes at both local and landscape scales (Johnson, 1980; Senft et al., 1987; Spake et al., 2020), therefore woodland planting schemes would benefit from considering shifts in deer browsing pressure in response to planting designs. Mapped predictions of deer impact risk in response to alternative woodland creation scenarios could allow landowners to anticipate how changes in tree cover may affect the distribution of impact risk to woodlands, both for their local patch and the wider landscape. These visualisations of changes in risk across multiple spatial scales could facilitate landscape-scale collaboration and enable more targeted allocation of limited management resources.

Previous studies that have sought to predict ungulate impact risk have adopted statistical methods, using existing deer impact data and predictor variables characterising factors such as woodland structure, landscape composition, and deer density (e.g., Jarnemo *et al.*, 2014; Spake *et al.*, 2020; Brock *et al.*, 2023). While such models have revealed important drivers of current impact risk, they may predict

impacts poorly when extrapolating beyond the training data's environmental parameter space (Fordham *et al.*, 2018; Yates *et al.*, 2018). Continuing variation in deer densities and distributions (Croft *et al.*, 2019) in combination with future landcover transitions (Müller *et al.*, 2017) are set to generate novel deer species assemblages and landscape configurations across the temperate zone (Teixeira & Fernandes, 2020). Mechanistic modelling frameworks, such as Bayesian Belief Networks (BBN), which can model the relationships between landscape structure, deer behaviour, and woodland impact risk, offer a means to predict impacts in such novel landscapes. BBNs use expert knowledge to generate representations of the relationships between variables, and a corresponding mathematical description of the conditional probabilistic dependencies between variables (Newton et al., 2007). The advantage of this bottom-up approach is that it uses all possible parameter space: every possible scenario of all variable state combinations is considered when predicting the probability of an outcome, including those that may not yet exist. This enables outcomes to be predicted for novel situations, including alternative land use scenarios.

BBNs are widely used in interdisciplinary research aiming to simplify complex social-ecological problems and communicate potential management outcomes to practitioners, (Marcot et al., 2006), often in the form of decision-support tools (Allan et al., 2012; Grainger et al., 2017). By using pictorial representations of relationships between variables, their visual and intuitive nature make them a valuable tool for iteratively co-developing a model structure with a wide range of stakeholders, who can help inform variable selection and their linkages (Marcot et al., 2006; Penk et al., 2017). Increasingly, spatially explicit BBNs are co-developed to enable decision-makers to compare the possible outcomes of multiple potential management scenarios in a defined area (Coccoli et al., 2018, Gonzalez-Redin et al., 2016), and thus can be used to compare outcomes of alternative woodland creation scenarios.

In this study, we iteratively co-developed spatially explicit BBN models with deer researchers and management experts to predict the risk of deer impacts to woodlands across landscapes in England and Wales, integrating expert knowledge with scientific evidence. To facilitate and encourage application of model predictions in decision making, we co-developed an associated online interactive decision-support tool - the 'iDeer Tool' with experts and potential end-users https://ideer-

project.shinyapps.io/ideer/. Users of the iDeer Tool can explore maps illustrating the current risk of deer impacts to woodlands and assess changes to risk in response to user-specified woodland creation scenarios. The tool thus aims to support landowners and forest management organisations in considering how local scale woodland planting may influence landscape-scale woodland cover and encourage collaborative deer management efforts. The iDeer tool produces downloadable output maps for easy integration into relevant deer and habitat management plans and woodland creation and management grants. Finally, the approach provides a blueprint for co-developing spatial BBNs for mammal impact prediction that can be adapted for other wide-ranging species, geographic areas and land use decision challenges.

Materials and methods

2.1 Study area and methodological overview

We sought to develop a predictive model of deer impact risk for woodlands in England and Wales, countries with growing populations of six deer species: Red Deer (*Cervus elaphus*), Japanese Sika Deer (*Cervus nippon*), Roe deer (*Capreolus capreolus*), Fallow Deer (*Dama dama*), Reeve's Muntjac (*Muntiacus reevesi*), and Chinese water deer (*Hydropotes inermis*). Both countries have ambitious woodland creation targets: England to increase tree cover from 14.5% in 2023 to 16.5% by 2050 (UK GOV, 2022) and Wales to plant 180,000 hectares between 2021 and 2050 (Welsh Government 2021). Landscape-level management is challenged by fragmented landownership, differing land use objectives, and varying attitudes towards deer (Cini et al. 2025; Logan et al. 2025). Scotland was not included due to different landownership scales and legal frameworks that may alter landscape-deer relationships.

We employed a collaborative co-development approach and purposefully recruited an expert panel of scientists and practitioners from leading executive agencies and woodland charities across England and Wales. Our panel comprised 22 experts: individuals who actively perform or advise on deer management for both Government agencies (n = 10), and charities (n = 4), private sector wildlife consultants (n = 2), and researchers (n = 6). Model development was underpinned by a literature review and incorporated multiple rounds of expert elicitation (Figure 1);

using two questionnaires **(Supplementary S1)**, an in-person workshop to facilitate interdisciplinary dialogue **(Supplementary S2)**, and two rounds of semi-structured interviews **(Supplementary S3, S4)** were integrated into the final BBN models. Informed consent was sought from participants before participation in any questionnaire, workshop, or interview. Research was formally approved by the College of Environmental Science and Engineering Ethics Committee at Bangor University (coses2019hi01) and the School of Biological Sciences Ethics Committee at the University of Reading (SBS22-23 51).

Our resulting spatially-explicit BBN models comprise three components (summarised in Table 1): 1) an influence diagram representing dependencies between variables; 2) geospatial input layers used to define variables; and 3) conditional probability tables specifying probabilistic relationships between variables. Here we describe the iterative process of developing and validating these components. Table 1 outlines the systematic approach used to develop the iDeer BBN models, detailing key considerations and assumptions to facilitate replication for other taxa and geographic contexts. The Bayesian Belief Network model was scripted in R version 4.4.1 (R Core Team, 2024) using the bnlearn package (Scutari, 2010). Large language models (OpenAI, 2024) were used to improve code efficiency.
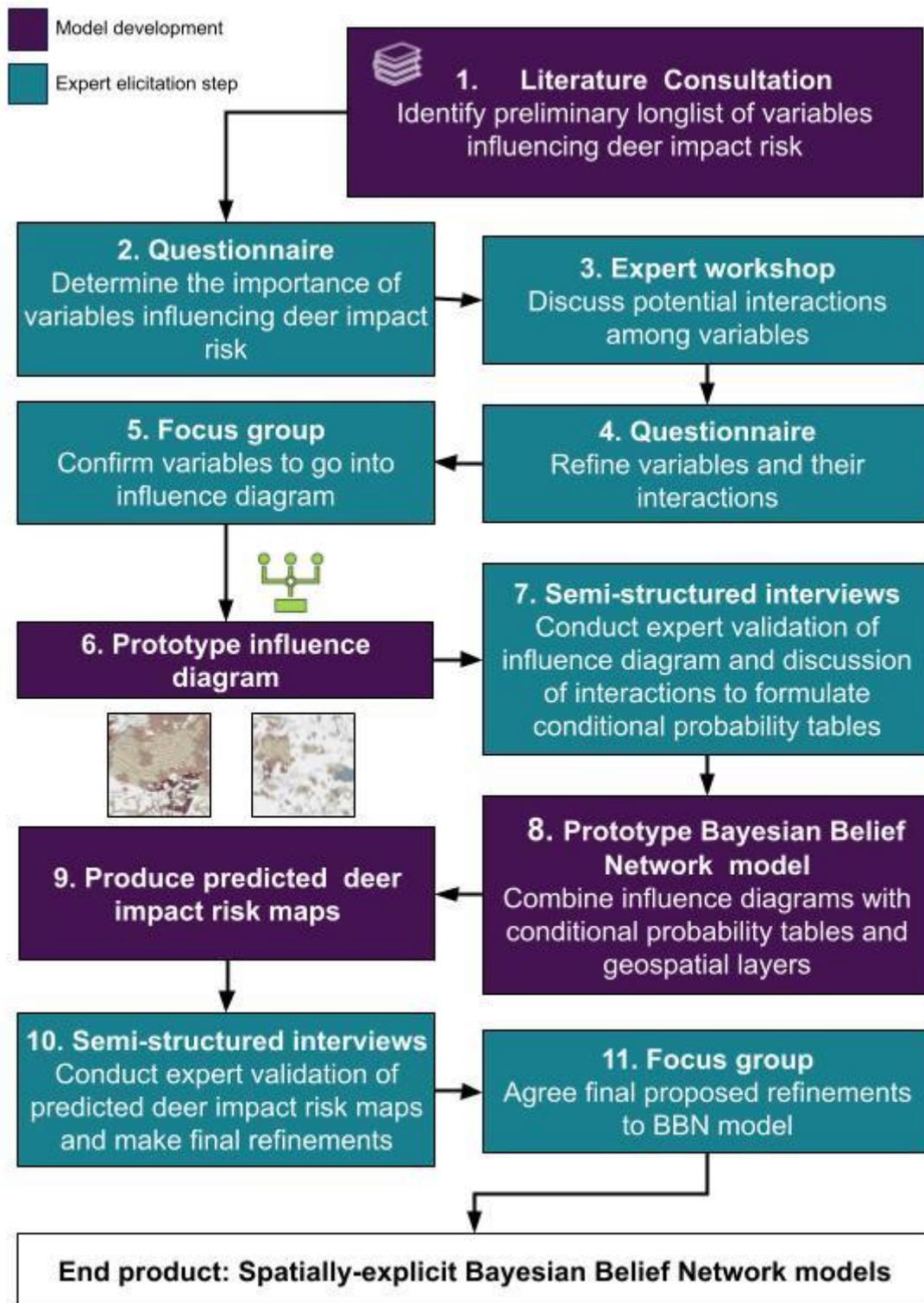
Figure 1: Chronological representation of steps used to co-develop and validate BBN models for predicting the risk of deer impacts to woodlands in England and Wales undertaken between April 2023 and May 2025.

Table 1. Overview of components of spatially explicit BBN models predicting risk of deer impacts to woodlands in England and Wales.

Component and description	Key steps and considerations in model development	iDeer BBN models
A) Influence diagram Pictorial representation of the relationships between variables. Variables (nodes) are connected by uni-directional arrows (edges), indicating conditional dependencies between the variables. Influence diagrams as depicted below include i) intermediate nodes (yellow), which are themselves influenced by ii) parent nodes (blue; and possibly other intermediate nodes), and iii) terminal nodes (red)- outcome variables for which BBNs predict the probability of their state, given the states of all other nodes.	**A1. Define outcome measure of interest (terminal node)**, ensuring relevance and interpretability by end users.	Deer impact risk was defined as the estimated deer activity experienced by a woodland area across a complete yearly cycle
	A2. Identify model assumptions and specificity Identify variables that cannot be measured, due to data availability, feasibility or cost constraints.	Deer density estimates are highly uncertain and fluctuate locally according to factors, such as management. Therefore, the iDeer BBN models do not include deer density as a variable, but instead make predictions under 'moderate' densities, at which deer preferentially select foraging locations.
	A3. Identify variables (nodes) and relationships The number of probabilities required to populate a Conditional Probability Table (CPT) grows rapidly with the number of parent nodes. To prevent overly complex CPTs, limit the number of edges going directly into the terminal node by using intermediate nodes, or "indices," that characterise the combined effects of multiple parent nodes (Marcot *et al.*, 2006). Seek to optimise model generality (robust applicability across space and time), realism (complexity) and accuracy (the difference between model predictions and the truth (Levins, 1966).	We identified intermediate nodes corresponded to key 'process' variables (Wisdom et al. 2020) which represent ecological processes related to energy acquisition and loss, and the associated habitat requirements for nutritional resources and shelter (Table 2). We developed two models distinguishing deer species by body size, assuming similar habitat preferences within each group: i) 'large deer' model (red, fallow, and Sika Deer) and ii) 'small deer' model (Roe, Muntjac, and Chinese water deer).
	B1. Relationship specification, including additive and conditional effects between variables	We employed a two-stage approach to specify CPTs: first initialising CPTs using expert-elicited relative importance weights

6

Component and description	Key steps and considerations in model development	iDeer BBN models
B) Conditional probabilities The direction, form and strength of each relationship are quantified through a set of probabilities. Conditional probability tables (CPTs) comprise a mathematical description of the conditional probabilistic dependencies between variables and factorise the joint probability distribution of all the variables.		for parent nodes, then assigning probabilistic node states using a Gaussian distribution to generate additive effects by default. Where semi-structured interviews indicated non-additive relationships between parent and child nodes, we modified CPTs to incorporate conditional effects rather than simple additive combinations.
	B2. Discrete state parameterisation (ranges corresponding to 'low', 'medium' and 'high' values)	Node discretisation was initialised by using natural breaks in variable distributions, followed by manual adjustments using expert input.
C) Spatial layers Geospatial layers representing nodes in the influence diagram	**C1. Define the scale at which to measure variables** Variables can be measured at multiple spatial scales.	Landscape-level variables were measured within circular extents surrounding each forest pixel. Buffer radii were 400-m and 1000-m for small and large deer models, respectively, due to differences in movement ranges. Variables were calculated at either 'local' (25-m resolution) or aggregated to the patch ('land parcel') level (see text for definition of land parcels), depending on the spatial scale at which deer respond to each factor. For example, digestible forage biomass was treated as a local variable, as deer select foraging locations at fine spatial scales, while the Thermoregulation Index was calculated at the patch level, reflecting deer selection of habitat patches for thermal shelter.

2.2 Iterative development of Bayesian belief network models
A. Influence diagram
A1. Define outcome measure of interest

Deer exert multiple impacts on woodland vegetation (Gresham et al., 2025), including: i) browsing on buds or foliage of woody trees and shrubs; ii) bark damage from stripping for consumption, scent marking, or cleaning velvet from antlers; iii) grazing of herbaceous understorey plants; and iv) trampling of soils and vegetation. Landowner acceptability of these impacts depends on their land use objectives (Reimoser & Putman, 2011). To facilitate broad applicability across landowners, we developed an impact metric independent of specific land use objectives.

Rather than attempting to model each impact type separately, we focused on predicting 'deer activity' as our target variable. This measure is commonly used by deer managers to indicate the amount of time deer spend in an area of woodland and is often assessed through field signs such as pellet density (Cooke, 2007; 2009). Deer activity is analogous to 'space use', used in movement studies, defined as the proportion of time per unit area spent by an animal or group of animals in the neighbourhood of a point in space (Matthiopoulos, 2001). From a mechanistic perspective 'deer activity' is widely used as a proxy for impact levels to woodlands (Cooke 2007; 2009). In our workshop, experts agreed this metric was a credible, scalable and generalisable means to simplifying assumptions of numerous nested linear relationships between deer activity and specific impacts and levels across differing landscapes of the countries in question. We therefore adopted the term "deer impact risk" as an interpretable measure that is consistent with established indices used across a range of woodland management objectives.

Impact risk levels exhibit substantial spatio-temporal variation across landscapes and within individual woodland stands (Schwegmann *et al.*, 2023). We therefore sought to quantify the overall deer impact risk across a complete yearly cycle within woodlands at 25-m resolution corresponding to the finest spatial grain achievable with available land use datasets and a sufficient granularity for typical woodland creation applications.

A2. Identify model assumptions

Whilst experts expressed a clear need to consider deer densities in predicting impact risk during the initial workshop, the relationship between deer density and impact risk is context-dependent, as evidenced by geographically variable 'density thresholds', critical densities above which management objectives, including natural regeneration, become compromised (Putman et al., 2011). In addition, deer density is not static and is subject to fluctuation over short timescales. We therefore developed BBN models without deer density as an explicit variable, instead operating under conditions of 'moderate' deer density across a particular area. Moderate density, therefore, corresponds to situations where deer are 'choosy' and exhibit selective space use, preferentially using areas with favourable characteristics (Borkowski, 2000). At 'high' densities, resource limitation would drive less selective foraging, resulting in deer using less preferred woodlands and undermining predictions based on local and landscape-level woodland predictors. Rather than defining 'moderate' density as a numerical range, we conceptualise moderate density as sufficient to cause woodland impacts, but not sufficiently high for impacts to occur uniformly across all available habitats regardless of their quality (Table 1). Our assumption of moderate density enables the prediction of differential impact risk based on local woodland and landscape attributes.

A3. Identify variables and relationships

The first step in producing a BBN is to illustrate a system as a graphical influence diagram (Table 1), in which variables (nodes) are connected by arrows (edges), suggestive of conditional dependencies between the variables (Figure 2). The number of probabilities required to populate the associated Conditional Probability Tables (CPTs) grow rapidly with the number of parent nodes, so we sought to limit the number of edges going directly into the terminal node by using intermediate nodes (Marcot et al., 2006). Following Wisdom et al. (2020), we identified key 'process variables', intermediate nodes that represent ecological processes related to energy acquisition and loss, and associated habitat requirements for nutritional resources and shelter.

To identify a preliminary set of process variables and their parent nodes, we reviewed published literature that related habitat selection by UK deer species to environmental predictors (e.g., Spake *et al.*, 2020; Jarnemo *et al.*, 2022; Brock *et al.*, 2023). We developed a formative questionnaire **(Supplementary S1a)** that asked experts to score the importance of variables in influencing habitat selection by each species to provide a basis for discussion at the in-person workshop (**Supplementary S2)**. During initial stages of model development (Figure 1), we explored the potential to develop models from maximum specificity (six species-specific models) to maximum generality (a single multi-species model).

Species-specific parameterisation was constrained by literature gaps (Gresham et al., 2025), and a lack of expert consensus on species' habitat preferences (as evidenced by responses to formative questionnaire: see **Supplementary S2**), particularly for Reeve's Muntjac and Chinese water deer. The Round 1 semi-structured interviews with experts (n=14; **Supplementary S3)** sought feedback on a preliminary influence diagram. Experts highlighted that a single influence diagram would be insufficient to predict impact risk, as inter-specific variation in foraging scale and dietary preferences strongly affects habitat selection. Consensus among semi-structured interviews identified body size as the primary determinant of these behavioural differences, leading to the development of two distinct models: a 'Small Deer Model' for small-bodied species (*C. capreolus, H. inermis, M. reevesi*, ranging in weight from ~9 to 25 kg; British Deer Society) with more localised movement within territories and diets specialised to woodland vegetation (Putman, 1988; Hofmann, 1989; Putman *et al.*, 2011), and a 'Large Deer Model', for large-bodied species (*C. elaphus, D. dama, C. nippon*, ranging in weight from ~30 to 200 kg; British Deer Society) with larger movement ranges and generalist diets. We used the feedback from the Round 1 semi-structured interviews to produce a final influence diagram considered credible by experts.

a) Influence diagram for Bayesian Belief Network model predicting impact risk to woodlands from small deer
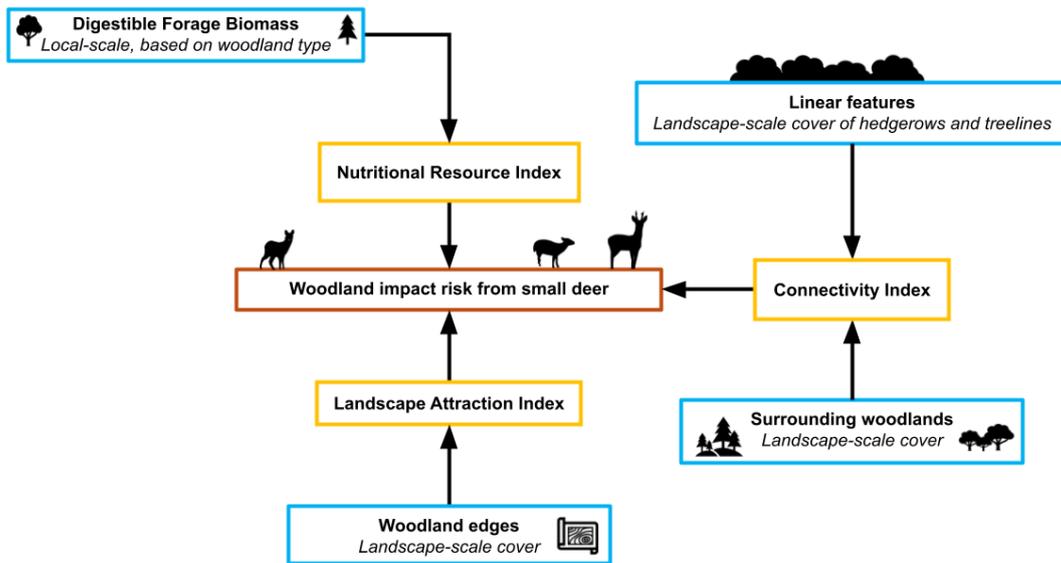
b) Influence diagram for Bayesian Belief Network model predicting impact risk to woodlands from large deer
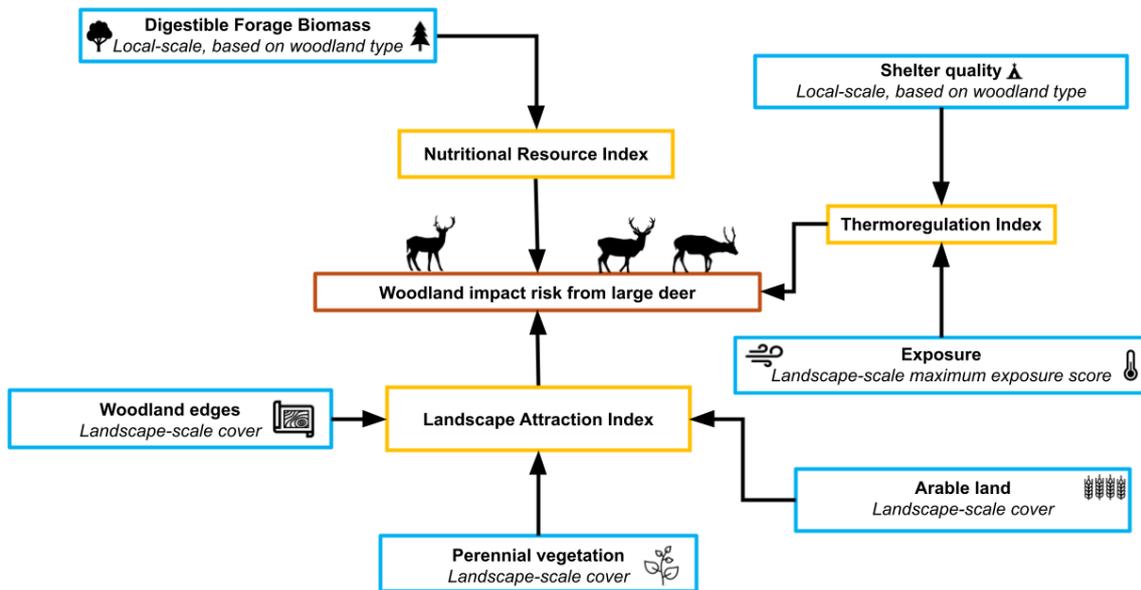
Figure 2. Influence diagrams summarising variables and their relationships in the final a) Small Deer Model and b) Large Deer Model. Landscape-level variables were calculated at 400-m and 1000-m extents for small and large deer species, respectively. Variables that represent ecological processes related to energy acquisition and loss, and the associated habitat requirements of deer for nutritional

resources and shelter are shown in yellow, with parent nodes in blue. The central terminal node, impact risk, for each model is shown in red.

B1. Relationship specification

Each node within a BBN has a defined set of discrete states (e.g., high, medium, low) and a corresponding conditional probability table (CPT) specifying the probability of each state occurring given all possible combinations of parent node states. When empirical data are unavailable, CPTs are commonly specified entirely through expert elicitation. However, full elicitation becomes prohibitive with large numbers of nodes and correspondingly extensive CPT parameterisation requirements (Hassall et al., 2019), particularly when parent node influences on child nodes are non-additive (i.e., there are interactions among nodes). To effectively engage experts in such activities, it is important to keep elicitation tasks relating to complex CPTs as constrained as possible in terms of labour and time required (Alkhairy et al., 2019).

We therefore employed a two-stage approach to CPT specification. First, rather than *de novo* elicitation of entire CPTs, we initialised CPTs using values of expert-elicited relative importance weights, providing a starting point for subsequent expert refinement. To initialise, parent nodes for each child node were assigned relative importance values (0-1, summing to 1), informed by discussions with experts during semi-structured interviews **(Supplementary S3).** Node states were then scored on scales of 1-3 or 1-5, corresponding to the number of defined states (high, medium, low or high, high-medium, medium, medium-low, low respectively). Importance scores were used to assign probabilistic node states to each CPT row using a Gaussian distribution ($\sigma = 0.41$). This process generated additive effects of parent nodes by default, with parent node contributions weighted by their relative importance. For example, three variables contributed additively to small deer impact risk with differing relative importance: Connectivity = 0.2, Landscape Attraction Index = 0.5, and Nutritional Resource Index = 0.8 **(Supplementary S5)**.

Where semi-structured interviews indicated non-additive effects of parents on child nodes, CPTs required modification to incorporate conditional effects. For example, in the Small Deer Model, the process variable Connectivity - determined by the two parent nodes 'woodland cover' and 'linear features' - was specified such that linear features were important only in landscapes with low woodland cover, serving a compensatory role in open landscapes. The addition of non-additive effects was also used to break ties in the case where multiple cells in a CPT contained the same probability value. The relative importance values for the Small Deer and Large Deer models are available in **Supplementary S5.** The CPTs for all variables are available in **Supplementary S6-S10.** The CPT values for parent nodes were 0.333 if the node had three levels (low, medium, high) or 0.5 if the node had two levels (e.g., medium, high).

B2. Discrete state parameterisation

Continuous variables were discretised into node states (Low, Medium, High) using a combination of manual and unsupervised discretisation (Beuzen et al., 2018). Histograms were produced for all variables in the influence diagram, for woodlands in England and Wales. State boundaries were first obtained using terciles or natural breaks in variable distributions. State boundaries were manually adjusted following the second round of semi-structured interviews to produce deer impact risk maps that more closely aligned with expert knowledge on risk distribution (**Supplementary S11-S12** for final threshold values).

C. Spatial layers
C1. Define the scale at which to measure variables

We measured variables at multiple spatial scales, reflecting the understanding that foraging location is influenced by processes operating at multiple scales (Johnson, 1980; Senft et al., 1987). Landscape-level variables were measured within circular extents surrounding each forest pixel. Buffer radii were 400-m and 1000-m for small and large deer models, respectively, reflecting that larger-bodied and more mobile species tend to use landscapes at broader scales to meet energetic and life history requirements (Putman, Watson and Langbein, 2011; Fattorini *et al.*, 2020).

Variables were provided to the BBN model at either a 'local' (25-m) resolution, or aggregated to a patch resolution, depending on the spatial scale at which deer respond to each factor. For example, digestible forage biomass was treated as a local variable, as deer select foraging locations at fine spatial scales, while the Thermoregulation Index was aggregated at the patch level, reflecting deer selection of habitat patches for thermal shelter. Further details of how variables were calculated are provided in the Results and Table 2.

Our outcome measure – deer impact risk – was predicted at 25-m resolution. To provide risk values at a scale appropriate for decision-making, values were aggregated (averaged) to woodland 'land parcels' represented as vector polygon boundaries in the National Forest Inventory (Forestry Commission, 2023) and the UKCEH Land Cover Map 2023 (Morton *et al.*, 2024b). The National Forest Inventory parcels include all woodlands over 0.5 hectares in area, with a minimum 20 percent canopy cover and minimum width of 20 metres. Parcels are classified by Interpreted Forest Type (IFT) using satellite imagery (see **Supplementary S13** for categories). We excluded all non-woodland categories, "Cloud / shadow" and "Uncertain" and then further divided them by UKCEH 'land parcels', units with a minimum area of 0.5 hectares, that can distinguish between forest under different management/species composition or separated by glades and rides. Land parcels were thus considered a suitable unit of aggregation through their representation of practicable local management units (Morton *et al.*, 2024b).

2.3 Predictive model validation

Model development and validation proceeded iteratively (Figure 1). Validation of complex expert-based BBNs must consider model structure, parameterisation and behaviour (Korb & Nicholson, 2010; Pitchforth & Mengersen, 2013). In the absence of suitable quantitative impact data for validation, we adopted a two-phase subjective validation approach, designed to ensure experts understood BBN mechanisms and that their inputs could effectively inform model refinement (Celio et al., 2012). The first phase ensured the 'conceptual validity' of the influence diagram, addressing the questions 'Are the foundations (theories and assumptions) of the model credible?' (Celio et al., 2012), and 'Does the model structure contain all and only the factors

and relationships relevant to the model output?' (Pitchforth and Mengersen, 2013). The second phase sought to establish the BBN's 'predictive validity' (Pitchforth & Mengersen 2013), and asked experts 'is the simulation credible?' (Celio et al., 2012) by presenting them with model outputs across multiple case study regions and identifying necessary improvements to ensure maps would provide credible representations of deer impact risk to woodlands. Refinements were made to the BBN models following these two phases of expert consultation.

A second round of semi-structured interviews (**Supplementary S4)** elicited expert feedback on the BBN's predictive credibility. Prior to the interviews, nine of the expert panel members provided coordinates for two to three landscapes where they had actively managed deer within the previous five years, plus one to two unfamiliar landscapes (familiar to other experts). Using these coordinates, we generated prototype deer impact risk maps between 3-8 square kilometres for each site using the prototype CPTs. The resulting risk maps were presented to nine experts during individual semi-structured interviews with AG (Figure 1). During these interviews, each expert was asked to evaluate qualitatively the credibility of the risk maps in terms of spatial distribution of predicted woodland impact risk across the familiar and unfamiliar landscapes, under an assumption of moderate deer density. Discussions were supported by reference to the BBN's influence diagrams and spatial input layers, including land cover maps and maps showing values of process variables. Based on these interviews, final adjustments were made to CPTs and thresholds for node discretisation. These modifications were presented during a final focus group (n=6) to establish consensus that the final BBN models would provide credible predictions of deer impact risk across landscapes in England and Wales (see **Supplementary S14** for presented slides detailing the final changes in the focus group).

2.4 Development of a user-friendly decision-support tool
End-user workshop

We held a workshop with potential end-users (n=6) of the iDeer Tool in the Elwy Valley region of North Wales. Participants were purposively recruited via the Game

and Wildlife Conservation Trust and Bangor University and included two woodland managers (one was also a deer stalker), one farmer, one council-employed ranger, one forester, and one conservation practitioner. Participants were asked whether they were currently using, or had previously used, any tools to help with land management, and for desirable features for the iDeer decision-support tool. Participants primarily expressed the importance of reliable land cover data, and a user-friendly interface that produces outputs rapidly. Participants also expressed preferences for mobile compatibility and Google Maps integration (full description of discussions in **Supplementary S15).**

RShiny user interface

We used the shiny R package (Chang et al., 2024) to develop an interactive web-based 'iDeer Tool' to allow users (landowners, land managers, and local authorities) to inspect model predictions for user-specified landscapes across England and Wales. The tool uses the BBN models to map deer impact risk to individual woodland parcels using information on woodland type and surrounding landscape characteristics, enabling comparison of alternative planting schemes and incorporation of deer considerations into 'Land Management Plans' required for woodland creation grants.

Users can move through the tool as follows:

1. Select a landscape. Users navigate and zoom on a UK map to select a landscape of interest. Users click on the landscape centroid, and specify the surrounding landscape size of interest, from 3-8 km^2 in size. This size range was chosen to encompass a range of landscape sizes of interest to landowners or local authorities (Deer Initiative, 2023) whilst balancing computational demands.

2. Identify deer species present. Based on the specified location, the tool identifies deer species present using presence-only data for each of the six species in England and Wales. Rasters (gridded maps) were generated using data from the British Deer Society (BDS) Deer Distribution Survey, with permission from the BDS. This survey collects presence-only data from public deer sightings at 10-km resolution. We merged survey data from 2005, 2010, 2016, and 2022 to produce a composite

presence-only 10-km raster for each species. Users can modify the species list if they have observed additional species not indicated by the distribution maps. The species list serves two purposes: (i) informing users of likely species presence for deer management planning, and (ii) determining which deer impact risk model to display (Small Deer and/or Large Deer Model).

3. View current impact risk. Geospatial processing generates and inputs spatially explicit nodes to the BBN models to predict impact risk. Users can visualise deer impact risk to existing woodland parcels within the selected landscape.

4. Model woodland creation scenarios. Users can draw polygons onto the existing land use basemap (OpenStreetMap contributors, 2017) to emulate a possible woodland creation scenario. the iDeer Tool then generates a new map showing predicted impact risk for all woodland parcels by recalculating geospatial input layers and re-running the BBN models. Newly planted woodland is classified as "Young trees" to align with National Forest Inventory categories (required for calculating the Nutritional Resource Index and Thermoregulation Index). To provide spatial units for aggregation comparable to existing woodland land parcels, newly-planted polygons exceeding 2.5 hectares are subdivided using Voronoi tessellation by creating 10,000 random points inside the new woodland polygon using sf:st_sample(), then k-means clustering around these randomly generated points using stats::kmeans() to divide the new woodland polygon into *n* pieces (n = new woodland area / 2.5 hectares).

5. Export outputs. Users can save maps as .png files for inclusion in Land Management Plans (required for woodland creation grant schemes in England and Wales (Welsh Government, 2024; UK GOV, 2025), or export as ESRI shapefiles (.shp) for use in other decision-support tools such as the Sylva Foundation's 'myForest app' that supports woodland creation grant applications (Sylva Foundation, 2025)

The iDeer tool includes a link to a feedback form and a central iDeer enquiries email address where users can provide feedback and suggest improvements for future development.

2.5 Case study generation

To demonstrate the tool's capabilities, we have selected an example landscape near the England-Wales border with opportunities for tree planting. The specified landscape contains pre-existing woodlands intermixed with semi-natural grasslands. We mapped current impact risk and generated future impact risk maps for two woodland planting scenarios: Scenario One comprised the addition of four large woodland blocks, and Scenario Two comprised the planting of 12, smaller woodland parcels. According to the British Deer Society deer distribution maps, the deer species present in this area include Roe, Muntjac, and Fallow Deer, necessitating impact risk maps from both the Small and Large deer models.

3. Results

3.1 Final Bayesian Belief Network models for predicting impact risk

Under the assumption of moderate deer density, two final BBN models were deemed to generate predictions that credibly represented spatial variation in impact risk and the change in risk following tree planting, for both large and small deer species across landscapes in England and Wales. The final Small Deer and Large Deer models each include three process variables (**Table 2**, **Figure 2**) characterising drivers of risk at local (25-m) and landscape scales, reflecting the understanding that foraging location is influenced by processes operating at multiple spatial scales (Johnson, 1980; Senft et al., 1987).

The models differ in the identity of process variables, parent nodes, and the spatial scale at which landscape-level variables were computed. For the Small Deer Model, landscape variables were characterised within a 400-m radius, representing the home range extent of small-bodied deer species (Barton *et al.*, 2023; Putman, 2024). For the Large Deer Model, landscape variables were measured within a 1000-m radius, reflecting the broader spatial scale at which large-bodied deer respond to landscape structure when selecting foraging locations (Putman, 2024; Fattorini et al, 2020).

Both models contain a 'Nutritional Resource Index', representing the local nutritional value of vegetation within a woodland pixel, and is determined by a single parent node, Digestible Forage Biomass. Deer impact risk is predicted to increase with the Nutritional Resource Index, as deer tend to select forage in areas with more digestible vegetation of high nutritional quality (e.g., Hebblewhite, Merrill & McDermid, 2008). Digestible Forage Biomass is determined at 25-m resolution by the woodland type, denoted by the NFI's 'Interpreted Forest Type' categories (**Supplementary S16**). NFI woodland categories with more open canopies, broadleaved, and earlier developmental stages are assumed to have greater digestible forage biomass (Ewald et al. 2014). For small deer, we distinguished three levels of digestible forage biomass (low, med, high), and two levels (medium and high) for large deer, reflecting the more generalist diet of large deer species **(Supplementary S13).**

The 'Landscape Attraction Index' indicates the nutritional value of the landscape surrounding an area of woodland, reflecting the positive selection by deer for landscapes (large deer) or territories (small deer) that contain nutritionally rich forage sources (e.g., high sugar crop plants and livestock pasture, semi-natural grasslands). In the Small Deer Model, attraction is determined by a single parent node, 'Woodland Edge', the percent cover of woodland edge habitat within 400-m of a woodland pixel. Edges support high digestible forage biomass and are often adjacent to additional foraging resources, encouraging greater foraging pressure (Saïd & Servanty, 2005; Lovari et al., 2017, Hjermann et al., 2024). Edges within contiguous woodland blocks but between different woodland types are also included (Kay et al., 1993). For the Large Deer Model, landscape attraction is determined at 1000-m by woodland edge and two additional parent nodes: the percentage cover of arable land and perennial vegetation, reflecting the importance of these foraging resources (Spake et al. 2020; Hurley et al. 2012).

A 'Connectivity Index' is included in the Small Deer Model, as experts emphasised that Roe and Muntjac are closely associated with woodland cover most of the time, and that highly connected woodlands have a higher impact risk. Connectivity was determined by two parent nodes: Woodland Cover (percent cover of woodlands) and

Linear Features cover (percent cover of hedgerows and treelines) within 400-m of a woodland pixel. Linear feature cover serves a compensatory role in determining connectivity, having a positive influence only when Woodland Cover is low (Morellet et al., 2011). Considered a patch-level variable (due to patch edges providing 'settling stimuli' that influence deer occupancy decisions at the patch scale, Gerhardt et al. 2013), connectivity values are averaged across individual woodland parcels, rather than 25-m pixels.

A 'Thermoregulation Index' is incorporated into the Large Deer Model to quantify the propensity of large deer to seek woodland shelter from climatic exposure, thereby increasing impact risk in shelter-providing woodlands. The Thermoregulation Index is determined by two parent nodes: 'Landscape Exposure' and 'Shelter Quality'. Landscape Exposure was quantified using the 'Detailed Aspect Method of Scoring' (DAMS; Quine & White, 1993; Pyatt & Ray, 2001), a metric originally developed to assess wind damage risk to forestry that can also serve as an indicator of exposure experienced by animals (Irvine et al., 2009; Spake et al., 2020). The maximum DAMS score within 1000-m of each woodland patch is calculated to indicate the presence of exposed terrain in the woodland's vicinity. Shelter Quality scores differentiate woodland types according to their capacity to provide thermal shelter, based on canopy openness and developmental stage (Ewald et al. 2014; Supplementary Material S1). Woodlands that provide high-quality shelter in exposed landscapes are at higher risk of impact (Barrett and Schmitz, 2013).

Table 2. Variables used in the final Bayesian Belief Network models to predict deer impact risk, and details of their spatial processing. NFI = National Forest Inventory (Ditchburn *et al.*, 2020; Forestry Commission, 2023). Process variables, which represent ecological processes related to energy acquisition and loss, and the associated habitat requirements for nutritional resources and shelter, are emboldened.

Variable	Model	Description and rationale	Details of input layers and spatial processing
Nutritional resource index	Small deer & Large deer	The nutritional value of vegetation within an area of woodland Woodland patches with higher nutritional resource value will have higher impact risk (Murray et al., 2016)	Values predicted at 25-m resolution by BBN
Digestible forage biomass	Small deer & Large deer	Woodlands with more open canopies and earlier developmental stages have greater digestible forest biomass (Ewald et al., 2014). Greater availability of digestible forest biomass will increase the nutritional value of the woodland for foraging deer	The NFI distinguishes 14 categories of woodland by their development stage and composition (broadleaved, coniferous or mixed). Woodland types were given forage quality scores that reflect the amount of high-quality forage likely to be present, in accordance with the amount of light that reaches the forest floor **(Supplementary S13, S16)**. 25-m resolution raster, extracted from NFI polygon
Connectivity Index	Small deer	The degree to which the landscape facilitates or impedes movement among resource patches. Higher connectivity leads to higher impact risk at the level of individual woodland patches.	Values predicted at 25-m by BBN. Averaged to woodland parcel level (see 2.3.6 for information on how woodland parcels were defined).
Woodland area	Small deer	Percent cover of woodland within 400-m of a woodland pixel Small deer rely on woodland cover for shelter and foraging; thus, landscapes with greater woodland cover provide more suitable habitat conditions, increasing connectivity across landscapes (Experts; REF).	A moving window approach (using raster::focalWeight() function) calculated the percent cover of woodland pixels within 400m of each focal woodland pixel.
Linear features	Small deer	Percent cover of hedgerows and treelines within 400-m of a woodland pixel. In areas of low woodland cover, hedgerows and treelines can facilitate movement of small deer through open land cover types (Experts; (Morellet *et al.*, 2011).	UKCEH Woody Linear Features Framework (Scholefield *et al.*, 2016) was rasterised to 25-m resolution. A moving window calculated the percent cover of linear feature pixels within 400m of each focal woodland pixel.

Landscape attraction Index	Small deer & Large deer	The nutritional value of the wider landscape surrounding an area of woodland, reflecting the positive selection by deer for territory establishment that contain nutritionally rich forage sources. Woodlands situated in landscapes with high forage quantity and quality are likely to be selected. Woodlands situated in landscapes that are more attractive have a higher impact risk (Hurley *et al.*, 2012).	Values predicted by BBN at 25-m pixel resolution.
Woodland edge cover	Small deer & Large deer	Percentage cover of woodland edge habitat within 400 metres (small deer) / 1000 metres (large deer) Landscapes with higher edge densities attract large deer due to provision of high amounts of digestible forage biomass (Hurley et al., 2012; Jarnemo et al., 2022; Miyashita et al., (2007). Landscapes with high edge densities can support more territories for solitary, small-bodied deer than landscapes with contiguous woodland, as edge habitats contain high biomass of digestible forage and represent the interface between closed woodland habitats and habitats with more open structure (Saïd & Servanty, 2005; Lovari et al., 2017). Consequently, woodlands situated in landscapes with higher edge density have a higher predisposition to deer impacts (Reimoser *et al.*, 2009).	NFI Interpreted Forest Types (14 categories) reclassified as either "open" or "closed" in structure (**Supplementary S16**). Boundaries between open and closed woodlands, and between woodlands and all other land uses, were identified using the boundaries() function from the raster package (Hijmans, 2023), resulting in a binary edge raster of 25m resolution. A moving window calculated the percent cover of edge within 400m of each focal woodland pixel.
Arable cover	Large deer	Percentage cover of arable land within 1000-m Deer strongly select landscapes with high arable cover due to provision of nutritional food resource (Jarnemo et al. 2022)	A moving window calculated the percent of arable land cover within 1000m of each focal woodland pixel. Arable cover was obtained from the 2023 UK CEH Land Cover Map (Morton et al., 2024a).
Perennial cover	Large deer	Percent cover of combined perennial land cover types. Deer positively select landscapes with high cover of perennial forage resources (grassland, heathland, bog and marsh) due to provision of diverse, nutritious food resources (Spake et al. 2020)	Perennial landcovers included semi-natural grassland, heathland and marsh land covers (see **Supplementary S17**). A moving window calculated the percent of arable land cover within 1000m of each focal woodland pixel.

			Perennial vegetation cover was obtained from the 2023 UK CEH Land Cover Map (Morton et al., 2024a).
Thermoregulation index	Large deer	The likelihood that large deer may seek shelter in an area of woodland. Impact risk is greater in woodlands with high thermoregulation index. Deer are more likely to seek shelter in woodlands that can provide shelter in highly exposed, climatically harsh landscapes (Mitchell, Staines, & Welch, 1977; Irvine et al. 2009; Spake 2020).	Index values predicted by BBN model at 25m pixel resolution for all pixels within NFI woodland patches
Landscape Exposure	Large deer	A metric indicating the degree of wind exposure. In more exposed landscapes, deer will have a greater need to seek shelter to thermoregulate to reduce energy expenditure needed to maintain homeostasis (Irvine et al., 2009; van Beest et al., 2021; Borowik et al., 2020; Mysterud & Østbye, 1999)	We used 'Detailed Aspect Method of Scoring (DAMS; (Quine & White, 1993; Pyatt & Ray, 2001): a metric for calculating risk of damaging winds to forestry, and previously used as a proxy for climatic harshness for deer (Irvine et al., 2009). DAMS is available at a 50-m resolution and is an ordinal representation of both mean wind speed and the frequency of strong winds and ranged from 3-36 across England and Wales. A moving window calculated the total (summed) DAMS score within 1000 m of each focal woodland pixel. Values were aggregated to the patch level by taking the maximum value of any patch pixel to indicate the presence of exposed terrain in the woodland's vicinity.
Shelter quality	Large deer	A metric that distinguishes woodland types in their capacity to provide shelter and buffer against climatically harsh conditions. Woodlands with more closed canopies have a higher capacity to provide shelter from elements and are therefore more likely to be selected than open woodlands in climatically harsh landscapes.	NFI Interpreted Forest Types (14 categories) reclassified for their shelter quality at the woodland parcel level **(Supplementary S18)** and rasterised to 25-m resolution.

3.2 Spatial variation in deer impact risk

Figure 3 shows the case study landscape on the England-Wales border with risk maps both before and after planting for two woodland planting scenarios. There is considerable variation in impact risk to woodlands across the specified landscapes, arising from variation in local and landscape-level variables, and their interactions.

Spatial variation in risk varies for the two species groups. Overall, impact risk to woodlands predicted using the Small Deer Model shows higher spatial variability across smaller extents compared to the predictions from the Large Deer Model. This reflects the difference in the relative importance of Digestible Forest Biomass across the models, as woodland type has a greater influence on impact risk from small deer than large deer, due to their specialist foraging habits (Figure 2, Figure 3). In contrast, landscape composition has a greater influence on impact risk from large deer, reflecting their more generalist grazing behaviour (Figure 2, Figure 3), and the larger extent at which landscape variables are characterised (1000-m, compared to 400-m in the Small Deer Model).

The contrast of impact risk scores between the planting scenarios demonstrates how differences in planting configuration influence the predicted risk from the two deer models. Figure 3 shows the change in impact risk to pre-existing woodlands, to demonstrate how the creation of new woodland can simultaneously increase and decrease impact risk to existing woodlands in a landscape. The small deer impact risk maps for woodland creation Scenario 1 and 2 show comparable increases in impact risk scores for pre-existing blocks within the spatial reach of the model predictions (400-metre radius), as connectivity and woodland edge area have substantially increased (Figure 3, Figure 4).

For the impact risk maps from the Large Deer model, both planting scenarios reduce the impact risk to pre-existing woodland parcels. This occurs because the new woodland is replacing perennial land cover, thereby lowering the Landscape Attraction Index. Scenario 1 shows a greater reduction in risk to pre-existing parcels compared to Scenario 2, as the larger areas of new planting in Scenario 1 the cause the greatest reduction in perennial cover within the 1000-metre radius of the spatial

processing and model predictions (Figure 3, Figure 4). In addition, any increase in edge area in Scenario 2 has a negligible effect on impact risk from large deer in this landscape, as edge amount is already high and has a relatively small influence on the Landscape Attraction Index compared to perennial and arable cover (**Supplementary S5).**
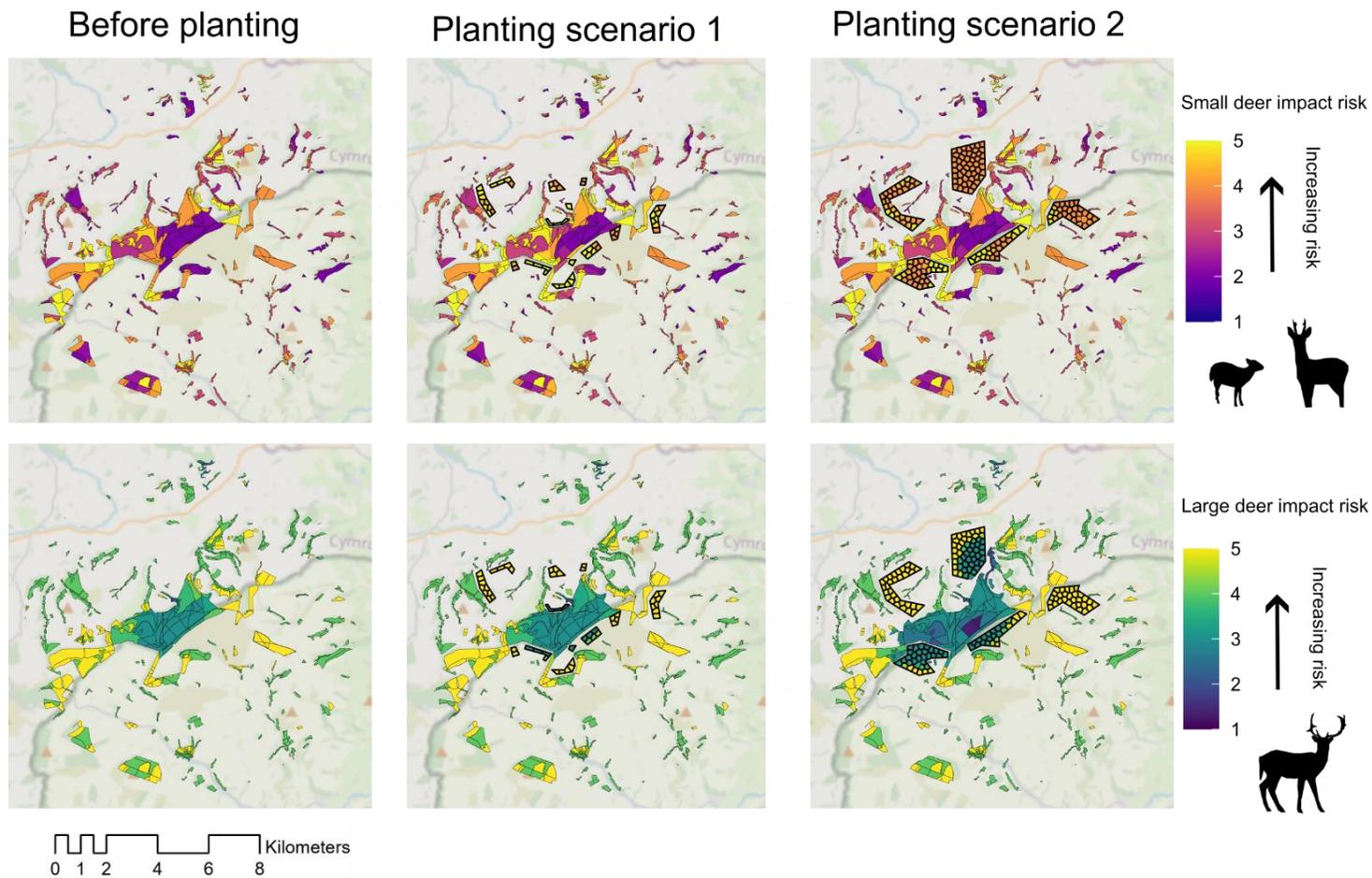
Figure 3: Deer impact risk maps for small deer (top row) and large deer (bottom row) from an area on the England-Wales border. Location: 52.48, -3.17. Risk scores range from 1 (low impact risk) to 5 (high impact risk). The two maps in column 1 show the current impact risk maps generated by the iDeer tool. Column 2 shows updated risk maps for a hypothetical scenario where 12 smaller woodland blocks have been

27

planted and split into Voronoi polygons (outlined in black). Column 3 shows updated risk maps following a second hypothetical planting scenario of four large woodland blocks, which are split into Voronoi polygons (outlined in black).
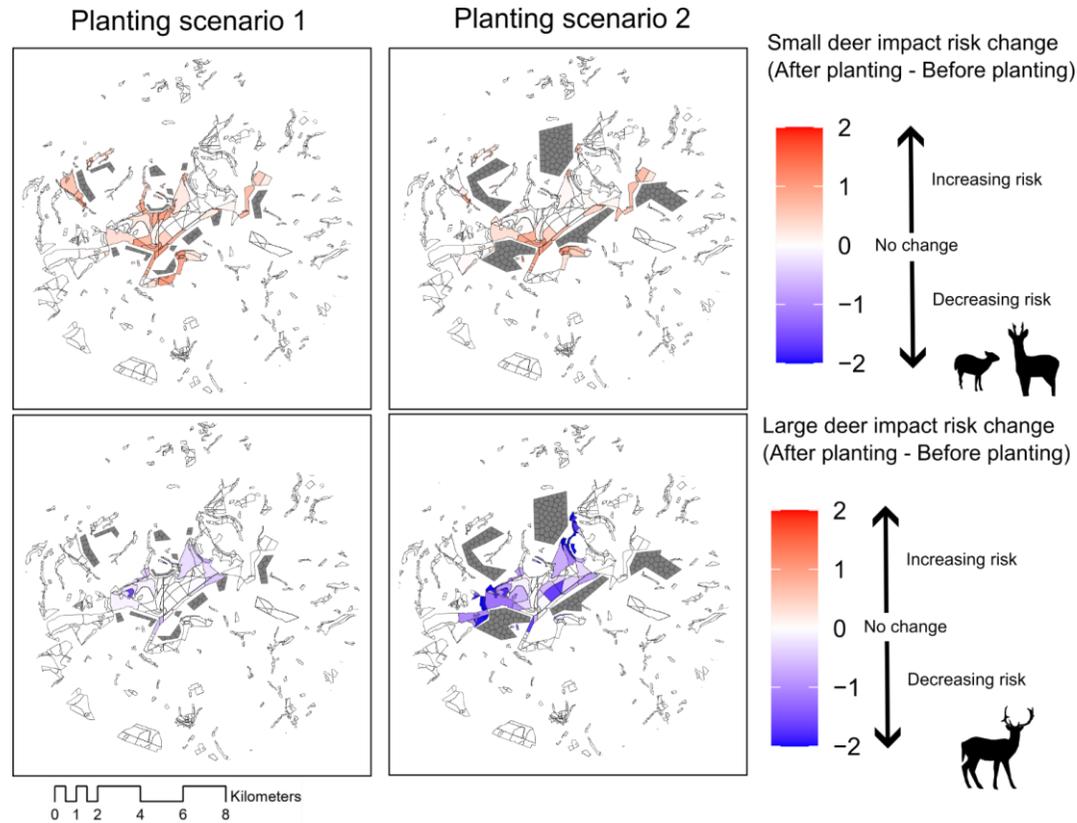
Figure 4: Change in predicted impact risk to pre-existing woodland parcels following woodland planting, for two scenarios and two species groups. Grey parcels represent newly planted woodland. Woodland parcels coloured in blue show reduced impact risk while red indicates increased impact risk. Woodland parcels coloured white have no change in risk following planting, assuming moderate deer density.

1 *3.2 The iDeer Tool*

2 The iDeer Tool (Shiny app) can be accessed online https://ideer-

3 project.shinyapps.io/ideer/. The iDeer RShiny application features many of the

4 desirable features identified in the stakeholder workshop (**Supplementary S15**). The

5 Tool is accompanied by a technical document and an Instruction Manual

6 **(Supplementary S19).**

7

Discussion

We present a decision-support tool for supporting woodland creation alongside deer in England and Wales. The deer impact risk maps help users to visualise deer impact risk to woodlands in their area of interest, anticipate the risk to newly planted woodlands and understand how woodland creation could change risk to existing woodlands in the landscape. The risk maps convey three principal insights. First, they demonstrate that deer impact risk to woodlands can be highly variable within a given landscape at moderate densities of deer, with woodland vulnerability strongly dependent on landscape context. The composition and structure of landscape surrounding a given parcel of woodland influence impact risk, through influences on processes related to energy acquisition and loss, and the associated habitat requirements for nutritional resources and shelter. Second, the distribution of deer impact risk across a landscape can change when new woodlands are created, with individual woodlands showing increases and decreases in impact risk in the same landscape. Finally, risk distribution varies by deer species groups, due to differences in the relative importance of landscape-level variables and their spatial scales of effect (Fattorini et al., 2020; Spake et al., 2020).

Risk maps can identify high-risk areas requiring enhanced sapling protection or alternative species selection at planting and highlight areas where deer stalkers could focus their efforts. They can also support landowners in strategically deploying costly deer fencing to the most vulnerable woodlands. Visualising how risk changes across broad extents (beyond a user's own land) could foster collaboration among neighbouring landowners, essential for effective landscape-scale deer management (Fattorini et al., 2020).

Model co-development highlighted insights on deer habitat selection in England and Wales that have yet to be documented in the literature. Research has reported negative associations between human infrastructure and activities with local deer density, space use and impacts in temperate landscapes (Mathisen et al., 2018; Zini et al., 2021; Wisdom et al., 2020). However, experts in this study emphasised that deer species in England and Wales have become more tolerant to human disturbance. Indeed, while our first iteration of the influence diagram (informed by the literature) included road density and proximity to residential areas (e.g., Meisinget et

al., 2012; Spake et al., 2020), experts agreed that these factors would have a weak influence on deer impact risk as defined in our study (Table 1). Smaller deer species can maintain territories in small woodland blocks very close to urban areas and can cope with disturbance by adjusting their activity budgets to avoid peak periods of human activity in recreational areas (e.g., Mirante et al., 2024).

Generalisation across species in deer management is challenging. To balance parameterisation needs with model generality and realism, it was deemed credible to distinguish between two species groups according to body size. Impact risk for some species may be more accurately predicted than others within these groupings. For example, Sika Deer are typically more solitary and more closely tied to woodlands than other large-bodied deer such as Fallow and Red Deer. For small-bodied deer, the Chinese Water Deer is a wetland specialist, while Roe and Muntjac are woodland specialists (Putman 2024). The ecology of Chinese Water Deer is poorly understood (Gresham et al., 2025), and the differences in habitat use between England and their native range remain undocumented.

Our models do not capture the outcome of multi-deer species assemblages. Where multiple deer species are both present at moderate densities in a region or landscape, our models may fail to capture variation in woodland impact risk arising from species interactions. Co-occurrence of deer species may alter the distribution of species-specific impacts in different contexts (Ferretti and Fattorini, 2020; Ratkiewitz et al., 2024). For example, one expert highlighted that in a region with high Fallow and Muntjac deer densities, these species tend to segregate their impacts to the edge and interior, respectively. Therefore, if land use objectives are to be met with a deer management plan, it is important to seek the advice of a deer management specialist, especially in an area with multiple co-occurring species.

We emphasise that the iDeer Tool is designed to support, not replace, professional deer management advice and field surveys for monitoring deer impacts. Our models do not incorporate local management interventions such as fencing that restricts deer movement or culling effort and locations (e.g., locations of high seats for shooting), because such information is not available at national scales. This limitation means our risk predictions may not credibly represent impact risk in areas with intensive management, as culling can induce 'landscapes of fear' that alter deer

habitat selection and foraging behaviour (Laudré et al., 2001; Palmer et al., 2022). Consequently, our outputs should be interpreted as baseline risk assessments that assume no active deer management interventions, providing a foundation for prioritising where such interventions may be most needed.

The iDeer models aimed to predict deer impact risk to woodlands as a function of landscape attributes. We distinguish our approach from habitat suitability models predicting the probability of deer occurrence at coarser resolutions, which do exist for UK deer species at 1-km resolution (Croft et al., 2019). While higher probability of occurrence could suggest more intensive landscape use and greater foraging pressure (e.g. Reimoser et al., 2009), such models do not reveal how risk is distributed among individual woodland parcels within a landscape at finer scales needed for woodland creation planning. Future empirical studies combining detailed impact assessments with species-specific deer activity data from GPS collars or camera traps across diverse woodland and landscape contexts would enable validation and refinement of these predictions.

The iDeer Tool

Our tool co-development approach offers a blueprint for addressing similar challenges with other mobile wildlife species in other geographic regions with limited data on densities and impacts. The BBN framework could be adapted to predict impact risks from species such as grey squirrels (*Sciurus carolinensis*), wild boar (*Sus scrofa*), or beavers (*Castor* species); species for which landscape-scale coordination of management is essential but challenging to achieve. It is important to note, however, that as digital decision-support tools proliferate in environmental management, practitioners face increasing 'tool overload'. Future tool development could prioritise integration with existing platforms and workflows rather than creating standalone applications.

Conclusions

The success of woodland expansion efforts depends not only on where trees are planted, but also the social and ecological interactions that determine tree growth and survival. The iDeer Tool produces spatially explicit models of deer impact risk, supporting land managers in landscape-scale decision making. By enabling users to visualise current risk and test alternative woodland creation scenarios, the tool

contributes to the proactive, coordinated approach essential for effective deer management. However, addressing deer impacts at the landscape scale will require more than improved risk assessment. While there is broad support for deer management in England and Wales (Cini et al., 2025), practitioners face challenges including insufficient grant funding for deer management, and limited skills and capacity within the sector. We encourage integration of deer impact risk assessments into woodland creation grant applications and planning processes as one component of a broader strategic approach to managing deer alongside afforestation goals.

Acknowledgements

Author contributions

A. Gresham led method development, data collection, analysis, results interpretation, and writing. R. Spake was the Principal Investigator and led conceptualisation and funding acquisition and contributed to method development, data collection, analysis, result interpretation and writing. M. Grainger, C. Bellamy, F. St. John, G. Shannon, F. Eigenbrod, A. Ward, P. Orsi and C. Nichols contributed to conceptualisation, funding acquisition, method development and results interpretation. E. Cini contributed to conceptualisation, method development and results interpretation. E. Cini led the organisation and method development of the Elwy Valley workshop, supervised by F. St. John. M Guy, A. Rattey, M. Grainger and C. Bellamy contributed

Data availability

All code required to reproduce the iDeer Tool and current deer impact risk maps are available in the following Github repository: https://github.com/amygresham48/ideer

The current deer impact risk maps are available as spatial layers in the following EIDC Data Deposit: **[LINK TBC]**

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Supplementary Information

S1: Expert questionnaires

a) The aim of the first questionnaire was to collate expert knowledge on factors affecting habitat use and foraging by deer. Anonymised answers were discussed during the workshop.

b) The aim of the second questionnaire was to collate expert knowledge on species-specific factors affecting connectivity and movement, and relative forage quality provided by different land cover types.

S2: In-person workshop slides

The aims of the workshop were to discuss the results of the first questionnaire (Supplementary S1), then ask a series of broad questions to draw on expert knowledge of the panel and build an initial Bayesian Belief Network influence diagram.

S3: Round 1 Semi-structured interview script and slides

Aim: To elicit feedback from deer experts on the structure of a Bayesian Belief Network model that will underly the iDeer decision-support tool.

a) Interview script

b) Accompanying slides

S4: Round 2 Semi-structured interview script and slides

Aim: To obtain feedback on mapped outputs from the Bayesian Belief Network models for Small Deer impact risk and Large Deer impact risk

a) Interview script

b) Accompanying slides

S5 Relative importance values

Relative importance values and non-additive effects specified in CPTs for a) the Small Deer model and b) the Large Deer model which contained more than one input node.

a)

CPT	Input nodes	Relative Importance Value	Non-additive effects	Non-additive effects justification
Connectivity Index	Woodland % cover within 400m	1	If woodland cover = High, reduce importance of linear features to 0. If woodland cover = Medium, reduce importance of linear features by 75%	Linear features are not important for connectivity if there is high woodland cover in the landscape.
	Linear feature % cover within 400m	0.6		
Impact risk	Connectivity Index	0.2	None	NA
	Landscape Attraction Index	0.5		
	Nutritional Resource Index	0.8		

b)

CPT	Input nodes	Relative Importance Value	Non-additive effects	Non-additive effects justification

Thermoregulation Index	Exposure	1	None	NA
	Shelter quality	0.2		
Landscape Attraction Index	Arable % cover within 1000m	1	If Arable % cover = High, increase importance of Arable % cover x 10	These effects ensured that where there was high availability of perennial and/or arable foraging resources, this would massively increase the attractiveness of the landscape.
	Perennial % cover within 1000m	1	If Perennial % cover = High, increase importance of Perennial % cover x 10	
	Woodland edge % cover within 1000m	0.1		
Impact risk	Thermoregulation Index	0.2	If Thermoregulation Index = Low, reduce importance by 1%.	The reduction of thermoregulation importance by 1% broke a tie between Med-High/High in one row of the CPT which led to "speckling" in the raster layer pre-extraction.

Increasing importance of attraction by 20% if it was high ensured that impact risk reached the higher risk categories on the map. |
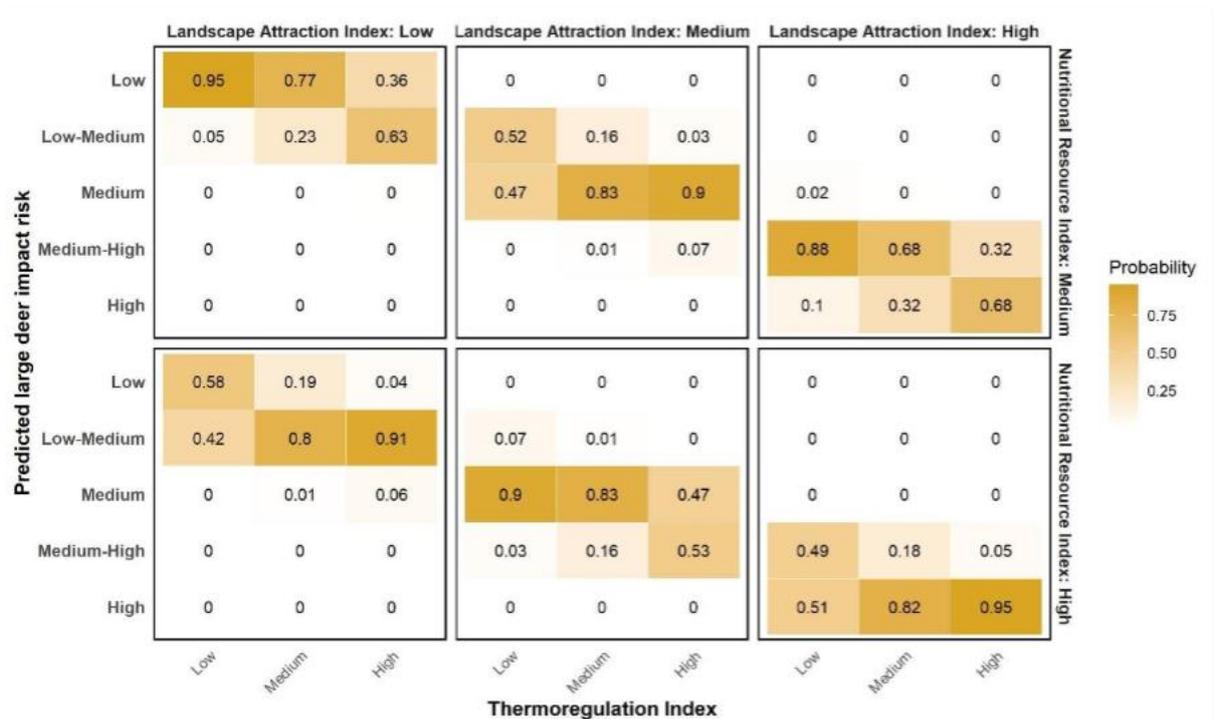| | Attraction Index | 1 | If Attraction Index = High, increase importance by 20% | |
| | Nutritional Resource Index | 0.3 | | |

S6: CPTs for predicting impact risk

Conditional Probability Tables used to predict impact risk to woodlands for a) the Small Deer BBN model, and b) the Large Deer BBN model. Values are probabilities of impact risk scores.
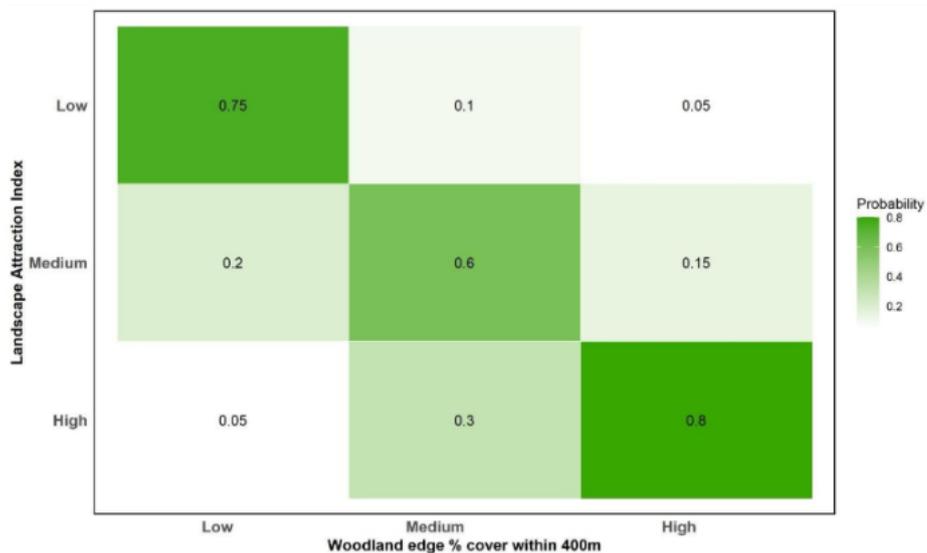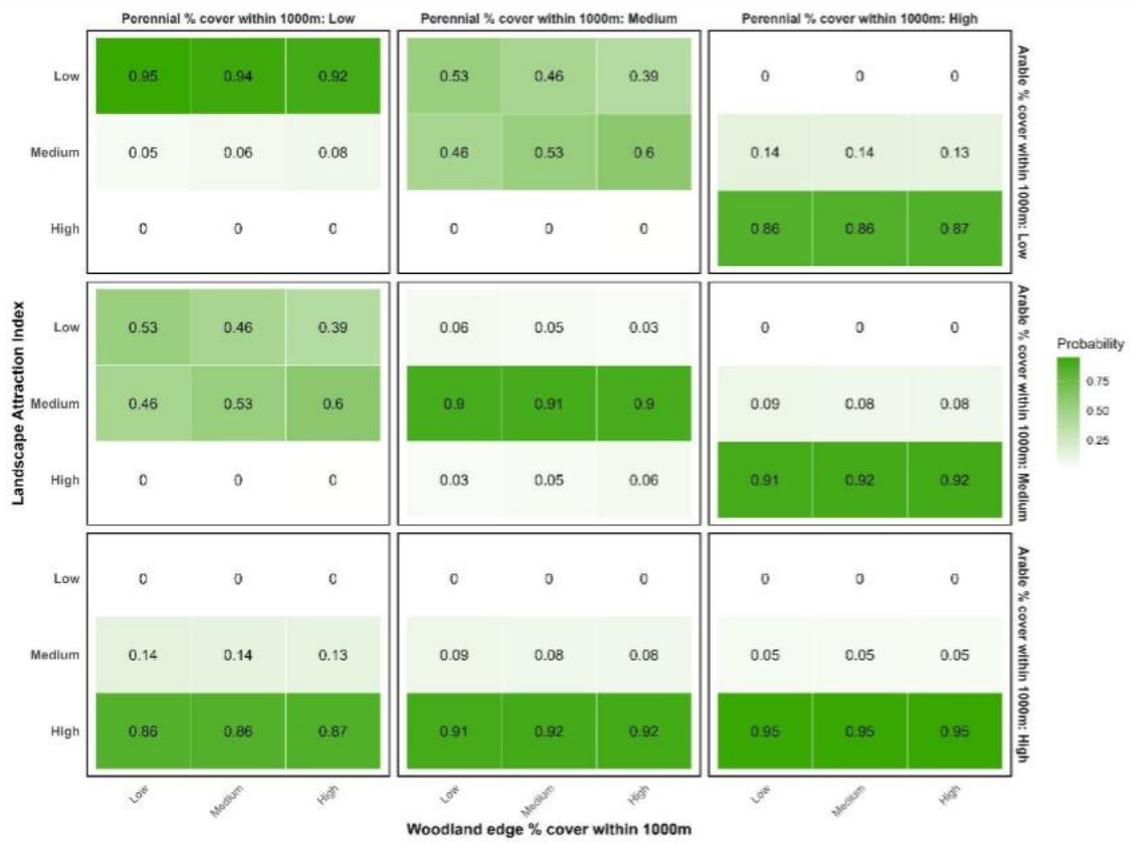
a)
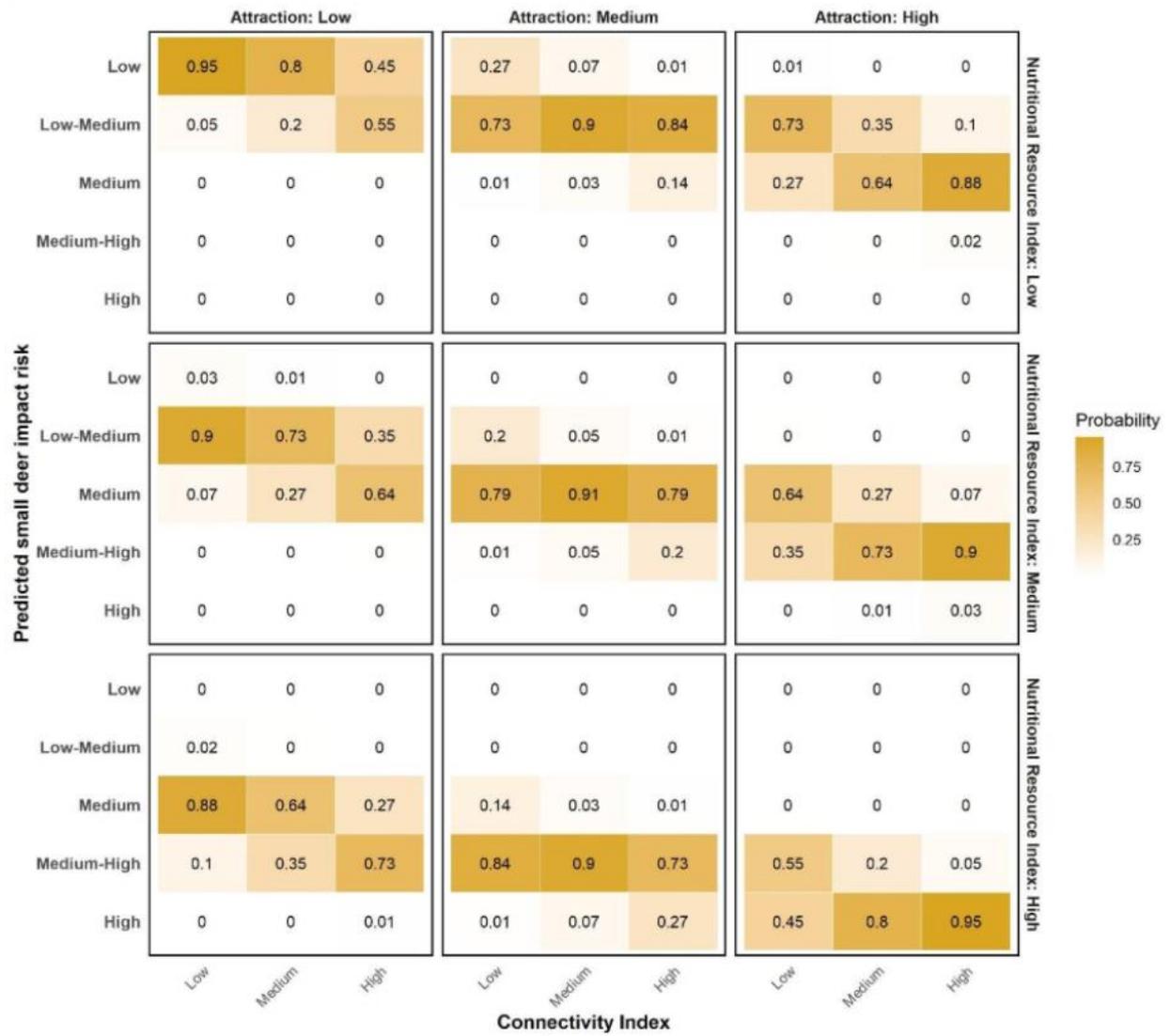
b)

S7: CPTs for Landscape Attraction Index

Conditional probability table for the Landscape Attraction Index for the a) the Small Deer BBN model, and b) the Large Deer BBN model. Values are probabilities of impact risk scores.
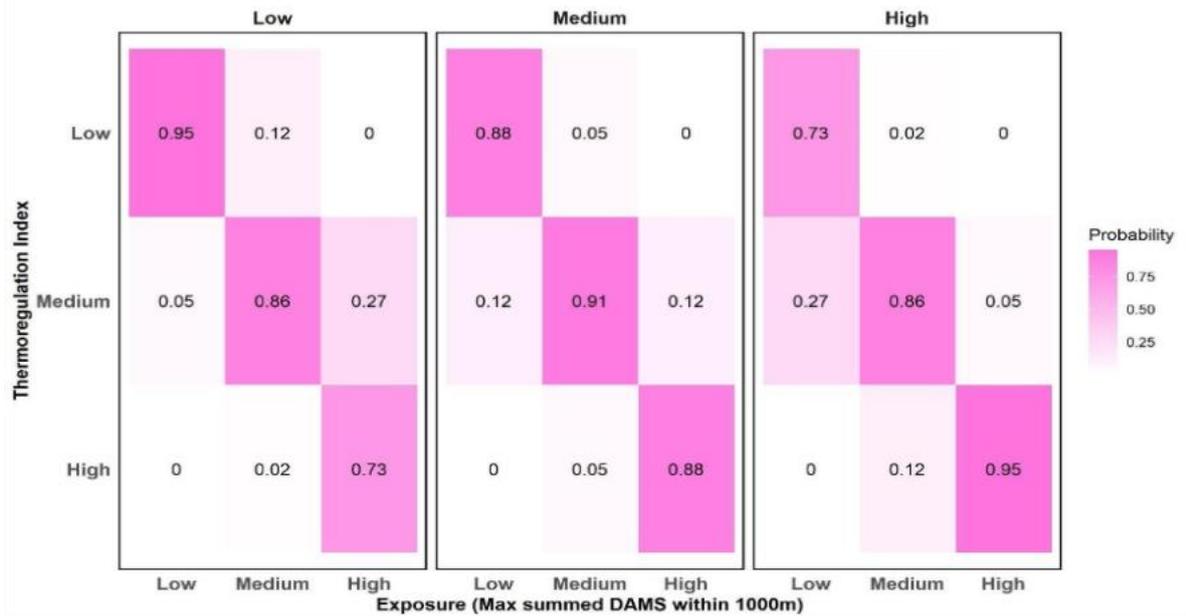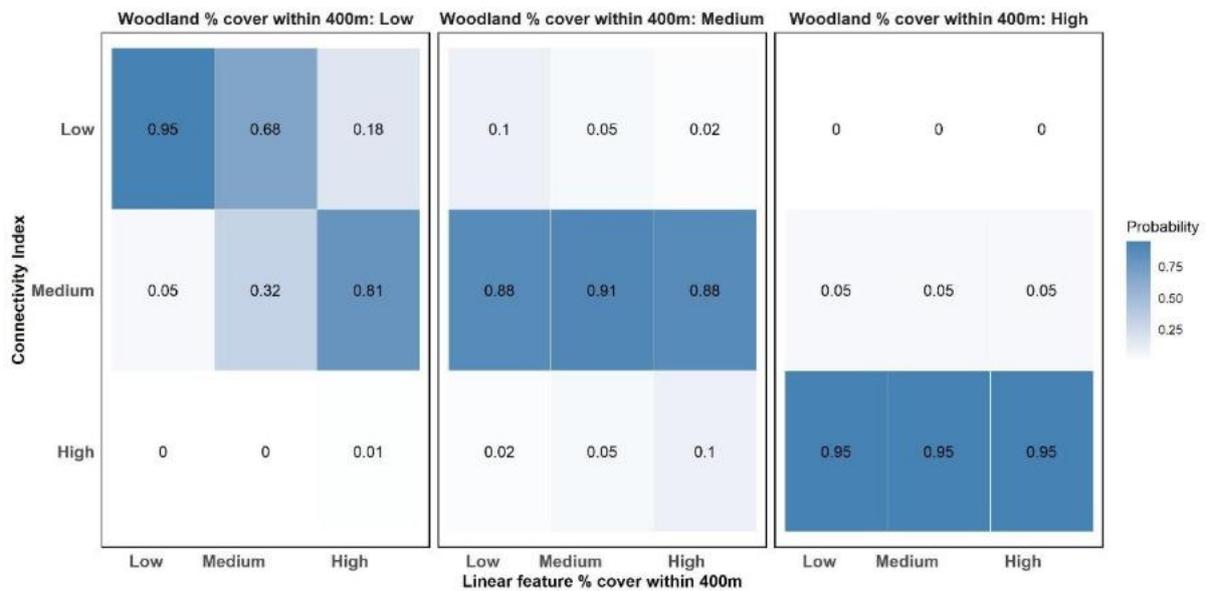
a)

b)

S8: CPTs for Thermoregulation Index

Conditional probability table for the Thermoregulation Index for the Large Deer BBN Model.
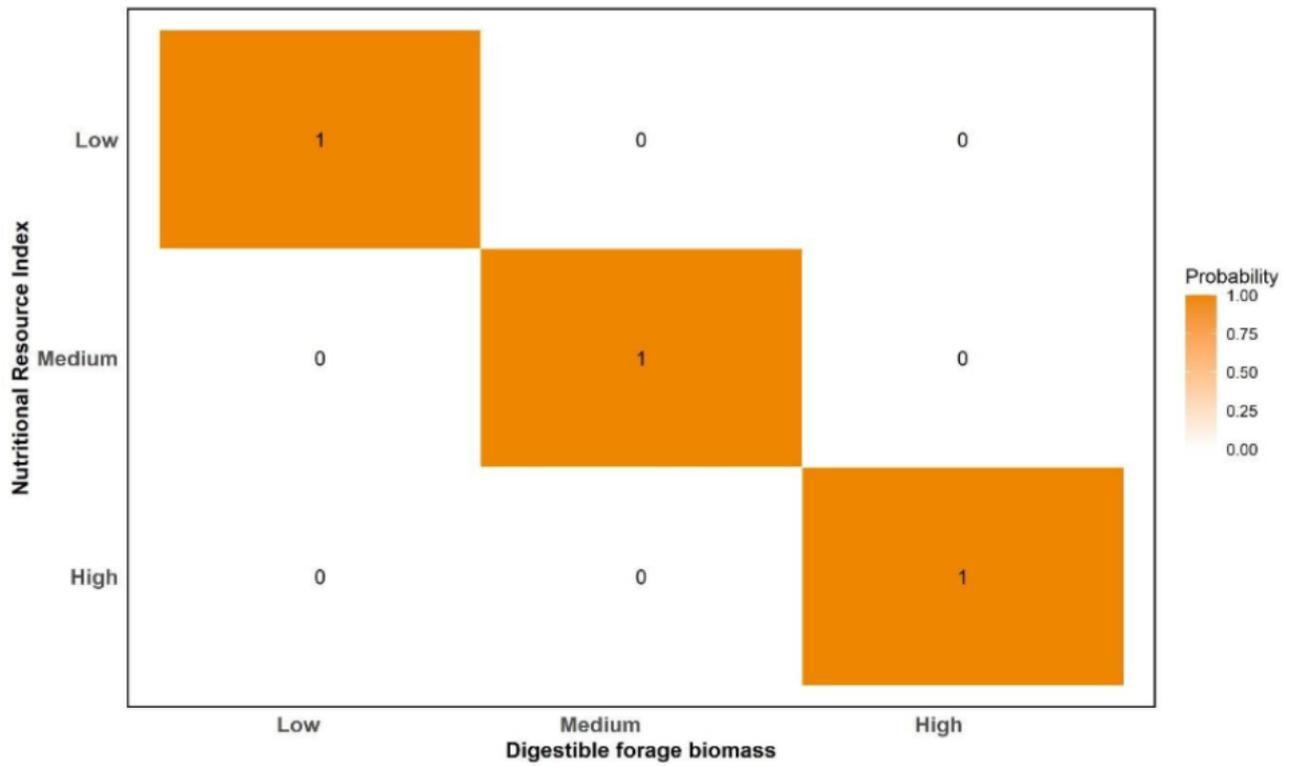

S9: CPT for Connectivity Index

Conditional probability table for the Connectivity Index for the Small Deer BBN Model.
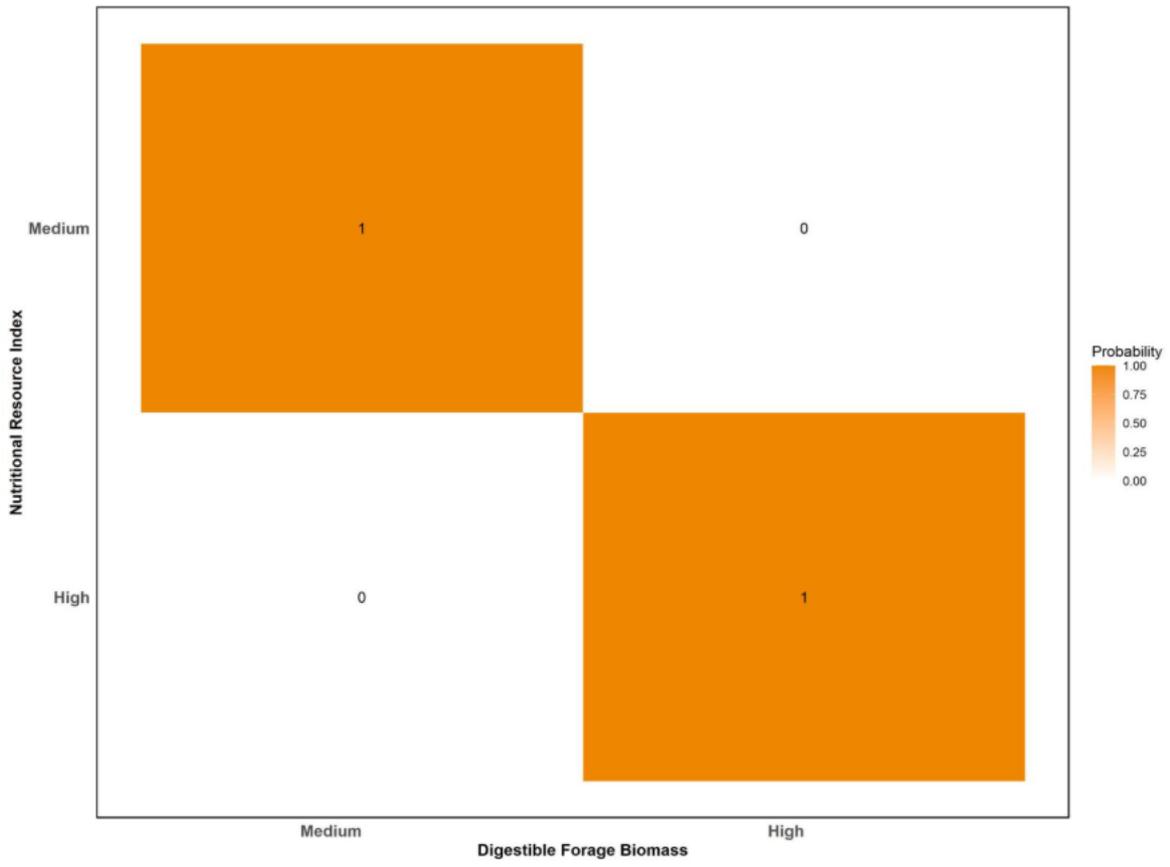
S10: CPT for Nutritional Resource Index

Conditional probability table for the Nutritional Resource Index for the a) the Small Deer BBN model, and b) the Large Deer BBN model. Values are probabilities of impact risk scores.

a)

b)

S11: BBN node value thresholds for Small Deer model

Thresholds used for converting continuous variables into categories for the BBN model predicting small deer impact risk

Variable	Low	Medium	High
Percentage cover of woodland edges within 400m	<=5	>5 & <=30	>30
Percentage cover of linear features within 400m	<=1	>1 & <=5	>=5
Percentage cover of woodland within 400m	<=2	>2 & <=10	>=10

S12: BBN node value thresholds for Large Deer model

Thresholds used for converting continuous variables into categories for the BBN model predicting large deer impact risk

Variable	Low	Medium	High
Percentage cover of woodland edges within 1000m	<=5	>5 & <=20	>20
Percentage cover of arable within 1000m	<=0	>0 & <=50	>50
Percentage cover of perennial within 1000m	<=25	>25 & <=50	>50
Maximum summed DAMS within 1000m (normalised from 0-1)	<=0.6	>0.6 & <=0.80	>0.80

S13: NFI Interpreted Forest Types ranked by Digestible Forage Biomass

Interpreted Forest Types (IFT) in the National Forest Inventory 2023 dataset categorized by their Digestible Forage Biomass (DFB) for small deer (Roe, Reeve's Muntjac, Chinese water deer) and large deer (Fallow, red, sika). Note: Assumed woodland represents areas where a woodland planting scheme has recently been established or is being planned, therefore Assumed woodland is treated the same as "Young trees" in the context of the models.

IFT	DFB for small deer	DFB for large deer
Broadleaved	Medium	Medium
Mixed mainly broadleaved	Medium	Medium
Conifer	Low	Medium
Mixed mainly conifer	Low	Medium
Coppice	Medium	Medium
Coppice with standards	Medium	Medium
Assumed woodland	High	High
Failed	High	High
Windblow	High	High
Ground prep	High	High
Felled	High	High
Shrub	High	High
Low density	High	High
Young trees	High	High

S14: Final focus group meeting

Slides from final focus group following the semi-structured interviews for operational validation of the iDeer tool, detailing changes to be made.

S15: Elwy Valley end user workshop

Description of findings from Elwy Valley workshop with potential end users of the iDeer Tool (n=9)

S16: NFI Interpreted forest types categorised by physical structure

Interpreted Forest Types (IFT) from the National Forest Inventory (2021) classified by structure for the purpose of mapping woodland edge and estimating Digestible Forest Biomass and Shelter quality.

IFT	Structure type
Broadleaved	Closed
Mixed mainly broadleaved	Closed
Conifer	Closed
Mixed mainly conifer	Closed
Coppice	Closed
Coppice with standards	Closed
Assumed woodland	Open
Failed	Open
Windblow	Open
Ground prep	Open
Felled	Open
Shrub	Open
Low density	Open
Young trees	Open

S17: Land cover types classified as "Perennial" for the large deer model

UKCEH Aggregate Class	UKCEH Land Cover Class
Semi-natural grassland	Improved grassland
	Neutral grassland
	Calcareous grassland
	Acid grassland
	Heather grassland
	Fen, marsh and swamp
Mountain, heath and bog	Dwarf shrub and heath
	Bog
Coastal	Saltmarsh

S18: NFI Interpreted Forest types categorised by shelter quality

Interpreted forest type in the National Forest Inventory 2023 dataset, categorized by their value as shelter for the large deer species (Fallow, red, sika). Note: Assumed woodland represents areas where a woodland planting scheme has recently been established or is being planned, therefore Assumed woodland is treated the same as "Young trees" in the context of the models.

Interpreted Forest Type	Shelter quality
Broadleaved	High
Mixed mainly broadleaved	High
Conifer	High
Mixed mainly conifer	High
Coppice	Medium
Coppice with standards	Medium
Assumed woodland	Low
Failed	Low
Windblow	Low
Ground prep	Low
Felled	Low
Shrub	Medium
Low density	Low
Young trees	Low

S19 iDeer Tool

a) Technical documentation accessible via the iDeer Tool for information on how the tool was made.

b) Instructional manual for how to use the iDeer Tool.