Habitat suitability modelling for red deer (*Cervus elaphus* L.) in South-central Slovenia with classification trees

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Abstract

We study and assess the potential habitats of a population of red deer in South-central Slovenia. Using existing data on the deer population spatial distribution and size, as well as data on the landscape and ecological properties (GIS) of the area inhabited by this population, we develop a habitat suitability model by automated data analysis using machine learning of classification trees. We assume that the recorded observations of deer approximate the actual spatial distribution of the deer population reasonably well. The habitat suitability models for individual animals have the form of classification trees. The induced trees are interpreted by domain experts and a generic model is proposed. The generic habitat suitability models can help determine potential unoccupied habitats for the red deer population and develop guidelines for managing the development of the red deer population and its influence on the environment. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

Human activity has mostly negative influence on self-regulating processes in forest ecosystems. Co-operation between wildlife management and forest management in Slovenia could be better despite the fact that both share the same place for their activities. This discrepancy is reflected in the changed structure and composition of the herbal part of forest ecosystems and also in the non-natural structure and density of wildlife, particularly game animals. High quality timber production and a high number of high score antlers at the same place are illusory goals if the above mentioned management branches do not start to work together. This is a well-known problem all over the world and Slovenia is not an exception.

Problems related to the imbalance between the population size of ungulates and forest management escalated in Slovenia at the end of the 1960s.

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The natural regeneration of forests in the Southern, most forested part of Slovenia, came close to a halt (Perko, 1979). The body weight and the health condition of red deer (*Cervus elaphus* L.) and roe deer (*Capreolus capreolus* L.) were deteriorating (Simonič, 1982). Foresters and hunters were faced with a problem, which could only be solved with an interdisciplinary approach. The result of joint work was a more holistic wildlife management system that became known as 'the control method' (Simonič, 1982). They established a network of permanent plots for observing the degree of browsing of new growth in the forest. They also started with systematic measurements of several groups of parameters about the body size, health condition and location of shoot-off for every harvested animal in the South-central part of Slovenia. Based on the first analysis of the collected data, they decided for a large reduction of the red deer population size. They estimated that they reduced the population size by half. Unfortunately the degree of browsing didn't follow the trend of the red deer population size reduction.

The problem was just partly solved despite the fact that browsing effects of other ungulates (mostly roe deer) were eliminated from the observations of the degree of browsing. A reaction to this was a new approach to understanding of the processes in forest ecosystems. Motivated by the many positive results and experiences of applying artificial intelligence methods, and in particular machine learning methods, in ecological modelling (see e.g. Kompare et al., 1994; Kompare, 1995; Džeroski et al., 1998). Stankovski et al. (1998), used the approach of machine learning of regression trees (implemented in the tool RETIS) to analyse the interaction between population dynamics of red deer and forest development.

This work pointed out the important influence of meteorological parameters on the degree and location of browsing. It was shown that high temperatures and high quantity of precipitation during the summer, as well as high snow cover during the winter have significant influence on the degree of browsing. It was thus shown that the meteorological parameters lead to non-linear interactions between the state of the forest new growth and the size of the red deer population.

Debeljak et al. (1999) extend the research of Stankovski et al. (1998) by showing that severe climatic conditions during the summer and winter also have a negative effect on the body weight of red deer. They show that the quantity of precipitation during the summer has significant effect on the body weight of 1-year-old calves and that the weather conditions during the first winter are very important for the body size and health condition of the red deer in the second year of its life. It was also shown that the climatic conditions have an important influence on the body size and health condition of red deer until the age of 10 years.

After including meteorological information in the studies of red deer population dynamics, the next logical step is to take into account more information on the area where the studied population of red deer lives. This leads us to consider home ranges of red deer, as well as information from a Geographic Information System about the study area in South-central Slovenia. The two are combined to derive habitat suitability models by means of machine learning tools. This is the subject of the present paper.

Habitat models have become well-accepted tools for understanding the habitat characteristics of different organisms, evaluating habitat quality and developing wildlife management strategies (Verner et al., 1986). They become even more useful if they are linked with GIS and expert systems. In the field of GIS, expert systems help to design maps, to extract geographic data for use in GIS, to create databases and to support decision making. Loh and Rykiel (1992) support an integrated approach to environmental management that couples database management, GIS, and expert systems. Donovan et al. (1987) build models from GIS landscape data to evaluate nesting and brood-rearing habitats for wild turkeys. Walker (1990) used GIS data to inductively develop models of the presence or absence of kangaroos in relation to climate on a regional scale. Fabricius and Coetzee (1992) have used GIS and artificial intelligence for developing a prediction model for the presence or absence of mountain reebuck in Karoo arid dwarf shrubland in South Africa. Kobler et al. (1997) studied a brown bear ecological niche in the area of the Vrhnika–Pos-

tojna highway by a GIS analysis of radio-tracking data. Kobler and Adamič (1999) have used a combination of GIS and artificial intelligence for brown bear habitat modelling and identification of locations for construction of wildlife bridges across highways in Slovenia. The model focused on the brown bear migratory routes from its core area in Southern Slovenia towards Western Slovenia and the Alps region.

2. The data

The study covers the forest area of High Karst in the South-central part of Slovenia. The data used for red deer habitat-suitability modelling come from two sources. The first source was telemetric tracking of animals. The second source was an existing geographic information systems (GIS) database.

2.1. Telemetric tracking data

In 1997, three adult red deer females aged 4–8 years were captured and equipped by Telonics 600-g radio collars. Telemetric tracking of the animals started in April 1997 and was stopped after 12 months. The tracking was done by a radio receiver Wagener FT-290 (144–154 MHz) with a receiving antenna and a map of the area at scale 1:25 000. In order to obtain as precise a location of the animals as possible, each location was defined from at least four different directions. Each animal was located at least once per week. We collected more than 70 locations for each animal. The time at which the animals positions were estimated was chosen randomly during daytime. To minimise the effect of noise caused by imprecise location readings and by random excursions of the animals, we decided to use an estimate of the home range of each traced animal, instead of using the raw telemetric locations.

The home range for $P = 0.95$ (the area in which an animal can be found with probability 0.95 (Anderson, 1982)) for each animal was calculated by the use of the adaptive kernel method (Worton, 1989). The kernel method is a non-parametric method used for determining the utilisation distri-

bution and the home range from a random sample of locational observations made on an animal. The kernel estimator can be summarised as follows. A probability density function, namely the kernel, is placed over each data point and the estimator is calculated. Where the points (locations) are concentrated, the kernel estimate has a higher density than where there are only few points. The smoothing parameter determines how smooth the resulting function will be. If a low value of the smoothing parameter is used, fine detail of the data can be observed, while a high value obscures all but the most prominent features. The adaptive kernel method varies the smoothing parameter so that the areas with a low concentration of points are smoothed less than the areas with a high concentration of points. Acceptable accuracy of the kernel method is obtained with at least 50 time-independent locations of an animal (Cresswell and Smith, 1992; Seaman, 1998). The independency of the points can be tested by using the Schoener test (Schoener, 1981). The calculation and graphical presentation of the home ranges with the above mentioned method were done by the computer program Calhome (U.S. Forest Service, Pacific Southwest Research Station), which allows the use of the least squares method for determining the smoothing parameter.

2.2. The study area(s)

One of the three animals was captured southwest of Ljubljana in the forests of Ljubljanski vrh and the other two in the forest area near Kočevje (Fig. 1).

The 'Ljubljana' animal has two significantly different locations (summer and winter location) during the tracking period and thus two disjoint areas of the home range (which are quite far apart from each other). On the other hand, the two animals captured in the area close to Kočevje have home ranges that overlap and are likely related.

We thus chose two separate study (sub)areas, one close to Ljubljana and one close to Kočevje, which enclose the home ranges of the animals and some of the surrounding area, leaving wide margins in each direction.

Fig. 1. Study areas.

The study areas of the animals are shown in Fig. 1.

The study area near Ljubljana covers 89 600 ha (summer home range: 212 ha, winter home range: 696 ha). The study area near Kočevje covers 25 200 ha (home range for first animal: 544 ha and home range for second animal: 468 ha).

The two study areas are actually much bigger than the home ranges themselves. This is necessary for the creation of positive and negative examples for habitat suitability modelling by using machine learning methods. In short, pixels within the home ranges are positive examples, while pixels outside the home ranges are negative examples. The two home ranges of the Ljubljana animal are quite far apart, while the home ranges of the two Kočevje animals mostly overlap: this is the reason that the Ljubljana study area is much larger.

2.3. GIS data

Via a raster GIS with a 200-m spatial resolution the pixels in each study area were linked to the ancillary GIS information layers, including information from the following sources:

1. The CORINE Land Cover database (Heyman, 1993; Kobler et al., 1998). This is a vector database with a minimum mapping unit of 25 ha, showing 44 types of land cover features, identified from Landsat TM imagery. For our purpose the available categories were aggregated into four general land cover types, relevant to deer habitat suitability (forest, agriculture, other vegetated, settlement/other non-fertile).

2. A raster digital terrain model with a 100-m resolution (Surveying and Mapping Authority of Slovenia, 1995), from which slope, exposition and terrain roughness were derived.

3. The Forest inventory database (Forest Service of Slovenia, 1997). This is a set of forest compartment centroids, with different forest data attached. To cover the whole forest, we constructed thiessen polygons around the centroids. Inventory data on timber volume and percentage of coniferous tree species in the timber volume were used.

4. A vector map of settlements, digitised off a 1:50 000 map (Surveying and Mapping Authority of Slovenia, 1995), from which distance to nearest settlement was computed for each 200 m pixel.

Each pixel in the grid was described by the following attributes:
- Elevation (m),
- Exposition (° of azimuth),
- Slope (%),
- Proximity to settlement (m),
- Percent of conifers in the forest (%),
- Wood stock (m^3/ha),
- Forest: yes (1), no (0),
- Terrain roughness estimated by the Laplace values for the digital terrain model (DTM)
- Land cover: 1, forest; 2, other vegetated; 3, agriculture; 4, non-fertile.

The above-described attributes were the independent variables (attributes) used in the habitat suitability modelling.

Habitat suitability modelling was based on four dependent variables, representing the home ranges of the four tracked animals. A dependent variable had value 1 if the corresponding pixel was in the home range of the respective animal, and value 0 otherwise.

The resulting four datasets were considered in the following order:
- Summer habitat of Ljubljana animal
- Winter habitat of Ljubljana animal
- Habitat of 1st Kočevje animal
- Habitat of 2nd Kočevje animal

We applied the C5/See5 system for inducing decision trees to the above datasets and induced four models.

3. Learning decision trees with C5/See5

Classification trees (Breiman et al., 1984), often called decision trees (Quinlan, 1986), predict the value of a discrete dependent variable with a finite set of values (called class) from the values of a set of independent variables (called attributes), which may be either continuous or discrete. Data describing a real system, represented in the form of a table, can be used to learn or automatically construct a decision tree. In the table, each row (example) has the form: $(x_1, x_2, ..., x_N, y)$, where x_i are values of the N attributes (e.g., elevation of a given location, its proximity to settlement, land cover at that location) and y is the value of the class (e.g., whether the location belongs to the home range of a given animal or not).

The induced (learned) decision tree has a test in each inner node that tests the value of a certain attribute, and in each leaf a value for the class. Given a new example for which the value of the class should be predicted; the tree is interpreted from the root. In each inner node the prescribed test is performed and according to the result of the test the corresponding subtree is selected. When the selected node is a leaf then the value of the class for the new example is predicted according to the class value in the leaf.

The common way to induce decision trees is the so-called top-down induction of decision trees (TDIDT, Quinlan, 1986). Tree construction proceeds recursively starting with the entire set of training examples (entire table). At each step, the most informative attribute is selected as the root of the (sub)tree and the current training set is split into subsets according to the values of the selected attribute. For discrete attributes, a branch of the tree is typically created for each possible value of the attribute. For continuous attributes, a threshold is selected and two branches are created based on that threshold.

Technically speaking, the most informative discrete attribute or continuous attribute test is the one that reduces most the entropy of the class variable. This is implemented in the notion of information gain (Quinlan, 1986), which is used to select attributes/tests. For continuous attributes, the values of the attribute that appear in the training set are considered as thresholds.

For the subsets of training examples in each branch, the tree construction algorithm is called recursively. Tree construction stops when all examples in a node are of the same class (or if some other stopping criterion is satisfied). Such nodes are called leaves and are labelled with the corresponding values of the class.

A number of systems exist for inducing classification trees from examples, e.g., CART (Breiman et al., 1984), ASSISTANT (Cestnik et al., 1986), and C4.5 (Quinlan, 1993). Of these, C4.5 is one of the most well known and used decision tree systems. Its successor C5 (Quinlan, 1998) represents the state-of-the-art in decision tree induction at the time of writing this article. The MS Windows implementation of C5, named See5, was used in our experiments.

An important mechanism in See5 used to prevent trees from over-fitting data is tree pruning. Pruning can be employed during tree construction (pre-pruning) or after the tree has been constructed (post-pruning). Typically, a minimum number of examples in branches can be prescribed for pre-pruning and confidence level in accuracy estimates for leaves for post-pruning.

We performed post-pruning of the induced trees (confidence level 1%), as well as pre-pruning. For pre-pruning, different numbers of examples were required for at least two branches, depending on the number of positive examples. For the Kocevje region, 39 examples were required for at least two branches. For the Ljubljana region, 15 and 50 examples were required for the winter and summer home ranges, respectively.

Another important feature of See5 is the ability to take into account misclassification costs: in some cases classifying a positive example as negative can be much more expensive than classifying a negative example as positive. In our case, positive examples are locations within the given home range. Since there are many more points outside the home ranges than inside, we have set the cost of misclassifying points that are inside to be much higher than the cost of misclassifying points outside the home range.

```
Elevation > 594:

:...Elevation <= 712:

  :...PercConifers > 59:

    :...Wood <= 190:

      :...ProxSet > 600:

        :...ProxSet <= 1780:

          :...Wood <= 110: InHomeRange
```

Fig. 2. Main branch of the tree for the Ljubljana — summer home range. Covers 49 of the 53 points in the home range.

```
Elevation <= 647:

:...Wood > 57:

  :...PercConifers > 9:

    :...ProxSet <= 2720:

      :...Forest = 1:

        :...Elevation <= 606:

          :...PercConifers > 54:

            :...Slope > 6: InHomeRange
```

Fig. 3. Main branch of the tree for the Ljubljana — winter home range. Covers 97 of the 174 points in the home range.

```
Elevation <= 580:

:...ProxSet <= 3102:

  :...Forest = 1:

    :...Elevation > 404:

      :...ProxSet > 1100:

        :...PercConifers > 51:

          :...Wood <= 139:  InHomeRange

        PercConifers <= 51:

          :...Wood > 157: InHomeRange
```

Fig. 4. Main branches of the tree for the Kočevje 1st animal home range. Cover 113 of the 136 points in the home range.

In the Kočevje region, where the size of the study area was 6300 pixels (corresponding to 200×200-m plots) of which only about 100 were inside the home ranges, we set this cost to be 500 times higher. In the Ljubljana region, where the size of the study area was 22 400 pixels, we set the misclassification cost for positive examples to be 2000 times higher.

4. Results

Decision trees were induced for each of the four home ranges, predicting whether points belong to the home range or not. The points in the home ranges were taken as positive examples, the remaining points of the respective study areas as negative. The GIS data described in the previous section were taken as attributes.

Figs. 2–5 gives the main branches for each of the four trees. These are the branches that contain most of the positive examples (points within the respective home range). Branches correspond to classification rules, also called if–then rules.

The four trees induced are models that represent the characteristics of the following four habitats:
- Summer habitat of Ljubljana animal (Fig. 2)
- Winter habitat of Ljubljana animal (Fig. 3)
- Habitat of 1st Kočevje animal (Fig. 4)
- Habitat of 2nd Kočevje animal (Fig. 5)

We should note that these are habitat models for the individual animals: they are under strong influence of the characteristics of the tracked animals and are not general habitat suitability models for red deer. The models relate the presence of

```
Elevation <= 564:

:...ProxSet <= 2550:

  :...LandCover = 1 (forest):

    :...Slope > 2:

      :...PercConifers <= 42:

        :...Elevation > 413: InHomeRange
```

Fig. 5. Main branch of the tree for the Kočevje 2nd animal home range. Covers 87 of the 117 points in the home range.

animals (and implicitly suitability of points in study area as habitat for the animals) to the geographic and vegetation characteristics of the points in the study areas.

The simplified model in Fig. 2 (only the main branch of the tree is shown) states that in summer, the Ljubljana animal mostly stays at elevations between 600 and 700 m, in forest with percentage of conifers greater than 60% and wood stock less than 110 m^3/ha, and at distance from settlements greater than 600 m. In winter, the same animal mostly stays at elevations under 600 m, in forest with wood stock greater than 60 m^3/ha and percentage of conifers greater than 55% (Fig. 3).

The 1st Kočevje animal stayed in the forest, at elevations between 400 and 600 m and further than 1100 m from settlements. It stayed in forest with percentage of conifers greater than 50% and wood stock less than 139 m^3/ha or in forest with percentage of conifers less than 50% but wood stock greater than 157 m^3/ha (Fig. 4). Finally, the 2nd Kočevje animal stayed in forests (LandCover = 1) with percentage of conifers lower than 42%, with terrain slope greater than 2°, at elevations 400–550 m (Fig. 5).

5. Discussion

The four models are different and reflect the individual characteristics of tracked animals and their environment/habitat. However, they are still somewhat similar and prompted us to postulate a generic model that would generalise the four individual models. While the four individual models were generated by machine learning, the generic model was postulated by humans, based on the four machine-derived models. If we try to explain the generic model from a wildlife expert point of view we have to be aware that making extrapolations from three animals to the population of red deer is very tentative.

The generic model summarises the common features of the four individual models.

It can be described by five attributes: elevation, proximity to settlements, presence of forest, percent of conifers in the forest and wood stock. The order of the attributes in the generic model is not completely defined by the four individual models, but we can observe some patterns of their interconnections, which have reasonable explanations.

First, the elevation in the individual models varies between 413 (Fig. 3) and 712 m (Fig. 2) above see level. We can explain this with the most suitable food and climatic conditions in this altitude belt. The regions under 400 m above the see level are under heavy pressure of urban and agriculture land use, which limits the red deer living activities in this region. Above 800 m the climatic situation changes drastically as compared to the lower altitudes. The climate above 800 m has already characteristics of mountain climate with a shorter vegetation period and thus the food capacity is lower then in lower areas.

The next attribute in the generic model is proximity to settlement, which ranges between 600 (Fig. 2) and 3102 m (Fig. 4). This shows that the tracked animals were in some way also present in the non-forest areas. This is probably related to sources of food like fields and forest edge.

Finally, two preferred types of forest emerge from the models, distinguished by the percent of conifers and the wood stock. These are clearest to see in Fig. 4. The threshold between them is somewhere between 42 and 49% of conifers in tree composition of the forest and around 150 m^3/ha of wood stock.

The first type of forest has high percentage of conifers and low wood stock. In severe weather conditions, especially in winter, red deer like to stay in young conifer forests, mostly spruce stands of age 15–35 years. This type of habitat has more suitable micro climatic conditions during the winter time than other, more open forest habitats, because of its closed and dense canopy layer (Ozoga, 1968; Telfer, 1978). The depth of the snow on the ground is lower due to its accumulation on the crown's layer (Kirchhoff and Schoen, 1987; Škulj, 1987). This habitat also offers some security for the animals because it hides them from carnivores and humans, which is not the case for the broadleaf stands during the wintertime (Fischer and Gossow, 1985; Nyberg, 1990). Young conifers stands are also sources of food, because there is a serious shortage of food in the forest due to the snow cower. Red deer browse on

the green branches and they stripe the soft, young bark from the trees (Škulj, 1987; Adamič, 1990, 1996). This has, on the other hand, negative consequences on the future economic value of the trees.

Forest stands with lower percentage of conifers and higher wood stock are typical summer habitats for red deer, particularly for milking hinds. This type of habitat has a well developed herbal layer with scrubs of new growth and offers much better food conditions than conifer stands. This is the reason why this type of the forest is so important during the summer for milk hinds with suckling calves, when they have explicitly higher demand for quality food (Clutton-Brock et al., 1982).

Our findings indicate similar patterns of living activities as in the habitat study of white-tailed deer by Patten and Sage (1999). They found that white-tailed deer also have summer and winter habitats. The reasons they state for the observed white-tailed deer behaviour are very similar to our explanations for red deer behaviour.

Summarising the generic model based on the four individual red deer models, we can state that there are spatial and temporal patterns of red deer activity that will help us in our further study of red deer habitats. We have to be aware of the limitations of extrapolations of our results on the population level, but we already have some good indicators of red deer habitat suitability and a lot of experiences for further study of this complex issue. The generic model also needs to be made more specific for extrapolation and determining potential deer habitat.

The modelling technique with machine learning has proved effective in combining telemetric tracking data with GIS data. However, the modelling results obtained in this fashion are limited by the quality of the input data. Large improvements are needed in this respect. We need to improve the GIS data about forest structure. We need more specific information about tree species composition of the stands, information about herbal and scrub layers, distribution of plant species communities (phytocoenoese) and their food capacity for red deer and other ungulates, locations of feeding places, forest management activities (time, type and locations of work in the forest), etc. We also have to improve the protocol of animal tracking in a such way that we will be able to identify sex, seasonal and night-time/daytime habitat characteristics of the tracked animals.

Using artificial intelligence, in particular machine learning methods, we have constructed individual habitat models for three female red deer from telemetric tracking data and GIS data on two study areas. While the models are very specific and highly individual, they have helped us to construct a more general habitat suitability model. The latter is reasonable from a wildlife expert's point of view and is closely related to another deer habitat suitability model (for white-tailed deer) developed from first principles. The characteristics of observed deer's home ranges will be used in our future research of potential deer habitats in a broader forest territory. The results are also in accordance with our expectations about their applicability in forestry management guidelines: the habitat characteristics of red deer can be used as constraints for carrying out forestry measures and can be included in short and long-term forestry management plans. We have thus moved a step closer towards establishing a natural balance between wildlife and forest management.

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