The Effect of Forest Cover Changes on Wild Boar Damage to Grass Fields in the Western Carpathians

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Abstract

Wild boar can root in farmland for food during times of scarcity, which can cause unpredictable and severe financial burdens to farmers. Although wider damage patterns may be attributed to boar abundance and density, there is a lack of consensus about the drivers of more localised patterns of damage. A factor that may be able to explain these differences is changes to local forest cover, which may influence the rooting attractiveness of certain fields for wild boar. In the Czech Republic and Slovakia, numerous changes to forest ownership occurred after the fall of communism, which altered the composition of the countries' respective forestry practices in the decades that followed. This research project therefore aims to investigate whether recent and/or past changes to local forest cover influence the presence and intensity of wild boar damage to grass fields in the Czech-Slovak border region of the Western Carpathian Mountains. Data was gathered using drone surveys of damaged and undamaged grass fields in the study region, which were mapped and analysed in ArcGIS Pro. Three generalised additive models were created in R to investigate whether changes to forest cover and other variables influence wild boar damage. Forests planted after 1985 were found to have a negative predictive influence on wild boar damage compared to those planted before 1985, while the proportion of human infrastructure and the proportion of current forest cover were found to have positive effects on damage predictions. A spatial analysis also revealed significant clustering of damaged and undamaged areas. The results of this research may be useful for wildlife management in the area, especially if combined with boar population data and modelling.

1. Plain Language Summary

Wild boar are native to Europe, but their numbers have been increasing in several countries since the 1980s. This increase is due to several reasons, such as a lack of natural predators in many regions, the spread of forested land, and possibly even climate change. Although wild boar play important ecological roles, their population growth has meant that they come into contact with humans more often, which sometimes creates points of conflict. For example, they can be involved in traffic collisions, spread diseases, and cause damage to agricultural land.

Damage to farmland from wild boar can be an expensive cost for farmers. Even if farmers invest in preventative measures such as “boar-proof” fencing, the success of these measures is not guaranteed. Obtaining compensation for damages can be a bureaucratically complicated process in many countries, which can leave farmers in the lurch if they do not meet the requirements. Furthermore, damage can be unpredictable: one field may be completely uprooted overnight, whereas its neighbour is left untouched. This makes it challenging to create fair management and support policies for farmers.

Aside from factors such as local boar numbers and hunting intensity, a detail that may be able to explain why damage occurs in some areas but not others is the past and recent changes to the local forest cover (i.e. deforestation and afforestation). Previous research suggests that wild boar prefer older and more intact forested landscapes than younger forests or cleared areas. Therefore, boars may prefer to root in fields that are located closer to these kinds of habitats.

Therefore, this research aimed to find out whether this was the case for wild boar damage to grass fields in the eastern border region between the Czech Republic and Slovakia, an area connected by the Western Carpathian Mountains. This region was chosen specifically as the two countries’ forestry practices underwent many changes following the split of Czechoslovakia after the fall of communism. The region therefore provides a good variety of forest history types from which to sample.

In order to answer this question, data was gathered from drone surveys of damaged and undamaged grass fields in the border region. Damages from these images were mapped and calculated using geographical software. Next, three statistical models were created with the aim of seeing if damage occurrence and intensity could be predicted by the history of the surrounding landscape. Other factors, such as the mean slope of each field, were also included in the models to see if they had an effect. Lastly, a simple spatial analysis was conducted to see if there were any damage “hotspots” in the region.

The results showed that forest history, local levels of urbanisation, and current local forest cover played significant roles in predicting fields damaged by wild boar. In addition to this, the spatial analysis revealed several hotspots and coldspots of damage - in other words, areas where damage was significantly more likely to occur (or not occur) within the region.

The results of this research not only shed light on the influence of landscape history on wild boar, but also tell us which areas are most at risk in the eastern Czech-Slovak border region. This information may be useful to farmers, wildlife management authorities, and local governments in the region. This research could be expanded in the future by integrating boar population data and by further developing the existing models.

2. Introduction

In Europe, wild boar (*Sus scrofa*) populations have steadily grown in many countries since the 1980s (Massei et al., 2015). This climb in numbers has been attributed to many reasons, including a lack of hunting and predators, increased reforestation, and climate change (Massei et al., 2015). These factors, coupled with the wild boar's adaptable nature and their relatively high tolerance for human activity (Faltusová et al., 2024), inevitably create points of interaction with humans, some of which lead to conflict.

Conflicts with wild boar can manifest in several ways, including in disease transmission, traffic accidents, and damage to property, including farmland (Massei et al., 2015). Damage to farmland is often the result of foraging or rooting behaviour. Foraging occurs when above-ground plant matter is more abundant (for instance, in cropland before the harvest season), whereas below-ground plants tend to be rooted in times of scarcity, such as during the winter season (Bongi et al., 2017). Damage can also be caused by trampling and lying (Drimaj et al., 2023; Find'o & Skuban, 2010). Such damage often results in high costs for farmers, who sometimes try to avoid such problems by installing preventative measures such as electric fences (Zhang et al., 2024). However, the efficacy of such measures varies greatly, and success in deterring wild boar from damaging fields is not guaranteed (Geisser & Reyer, 2004).

In the Czech Republic and Slovakia, damage caused to farmland by wild boar is also widespread. Both countries have experienced general increases in boar populations in the past few decades, although Slovakia has seen a decrease in numbers since 2023 due to increased hunting and an outbreak in African swine fever (Gočárová et al., 2025; Turek et al., 2018). Obtaining compensation for damages to fields can be a complicated process in both countries. In Slovakia, compensation is only provided if preventative measures are previously put in place by farmers, and claims must be made within 14 days (Find'o & Skuban, 2010). Compensation measures for damage also exist in the Czech Republic, but the payout to farmers is considered to be low (Bartoš et al., 2010).

Although boar damage to farmland has been extensively researched in many countries, there is little consensus on what the primary drivers of damage are. While population dynamics and other wider-ranging factors, such as the prevalence of hunting (Laguna et al., 2021), may explain distributions of boar on a macro scale, they do not always explain more localised patterns of damage. Anecdotal evidence from farmers received during this research project suggested that boar damage can be "random" in nature, with stories shared of one field being ploughed by wild boar overnight while the neighbouring field was left untouched for years. Numerous ideas to explain local patterns of damage have been posed by previous literature, such as the effects of soil type (Laznik & Trdan, 2014) and slope (Eshtiaghi et al., 2024). A theory that has been relatively under-researched is that boar damage is influenced by the history of the surrounding landscape, in particular concerning forestation. Some authors, such as Lee et al. (2018), postulate that boar damage may be driven by deforestation, which forces the boar to move into anthropogenic environments. Others, however, argue that boars prefer older, more intact forested landscapes as they provide more shelter and food opportunities (Drimaj et al., 2025; Haaverstad et al.,2013). Damage, therefore, according to these authors, is directly related to these conditions, as boars will root in fields that are located next to such environments. Therefore, there is plentiful discussion about the influence of forest history in mixed landscapes on wild boar damage.

In the cases of the Czech Republic and Slovakia, forest history is a very relevant factor to consider as the forestry practices of these two countries underwent significant changes following the fall of communism and the split of Czechoslovakia (Jarský et al., 2018; Munteanu et al., 2014). During the communist period, annual forest cover loss was high in Czechoslovakia due to the clearing of low-economic value forestry and shrubland for agricultural purposes. However, after the fall of communism, a large amount of agricultural land was abandoned due to a loss in profitability and a lack of agricultural subsidies (Munteanu et al. 2014). Since 1985, both countries have experienced a net forest increase of 4.2% and 2.1% respectively (Potapov et al., 2015), although this trend has experienced fluctuations due to bark beetle infestations in recent years (Hlásny et al., 2021). The changes to forestry practices, the rise in rural land abandonment, and the subsequent unplanned rewilding therefore make the two countries ideal locations to research the effects of changing forested and rural landscapes on landscape-level ecology.

Understanding therefore, whether forest-cover history plays a role in wild boar damage to fields today may help uncover new knowledge about the spatial dynamics and rooting behaviour of these mammals. In addition to this, mapping the damages in the eastern Czech-Slovak border region, an area that is connected by the Western Carpathian Mountains, may help to identify “hotspots” of where boar damage occurs. These insights could therefore be helpful to farmers, wildlife management services, and local governments in creating more targeted preventative and/or compensatory policies, while also contributing to the literature on boar damage in Central and Eastern European countries, which is less extensive compared to other locations.

Therefore, this research poses the questions:

1. How do recent and/or past changes to local forest cover influence the presence and intensity of wild boar damage to grass fields in the eastern Czech-Slovak border region of the Western Carpathian Mountains?

2. How are damage patterns spatially distributed in this region?

The hypothesis for this research is that boar damage will be more severe in areas that are home to older (pre-1985) forests, compared to areas that have experienced deforestation (either historic or recent).

In order to answer the first question, three generalised additive models (GAMs) will be constructed using data taken from drone imagery gathered in the eastern Czech-Slovak border region. The GAMs will be used to quantify whether boar damage can be predicted using forest history categories, as well as other relevant variables. To answer the second question, a spatial analysis will be performed in ArcGIS Pro by investigating the intensity of boar damage in the study region. This will be undertaken in order to identify any possible hotspots or cold spots of predicted damage.

3. Methodology

3.1. Study Area

The study region is located on the eastern side of the Czech and Slovak border region. It is 2812.71km2 and includes a 10.5km buffer area. It borders, but does not extend into, Poland. In the Czech Republic, the study area includes parts of the Moravia-Silesia and Central Moravia regions, whereas in Slovakia it incorporates sections of Trenčín and Žilina. The climate of the area is temperate and continental. Mean annual surface air temperature ranges from 6.71°C to 9.26°C, whereas annual precipitation is between 731.87mm and 1044.51mm (World Bank Group, 2025).

The primary soil type of the area is of the Cambisol group, but soils from the Umbrisol, Luvisol, Fluvisol, and Leptosol groups are also present (Akça et al., 2005). Cambisol soils are often rich in weatherable minerals, which make them ideal for agricultural purposes (Encyclopaedia Britannica, 1998). Approximately 10% of the land in the study area is made up of arable land, whereas 21% is composed of grass pastures. 57% of the area is covered by forests, the majority (54%) of which are coniferous. The area is very rural, with only 5% being categorised as urban infrastructure (Parente et al., 2021).

The study region is also home to other ungulates and large mammals besides the wild boar. Large carnivores such as lynx, bear, and wolves can be found on both sides of the border, although their distribution and population sizes vary across the region (Hackländer et al., 2021). Ungulates, including red deer, roe deer, and mouflon, are also found throughout the region (Bartoš et al., 2010; Find'o & Skuban, 2010).

3.2. Site selection

Drone surveys took place in permanent grass fields that were bordered by a forest edge. In order to find suitable sites, landcover datasets were examined and analysed in ArcGIS Pro. Two datasets of European forest cover were used to examine changes in forest cover from 1985 to 2020: the HILDA+ (Historic Land Dynamics Assessment+) dataset (Winkler et al., 2020), and a dataset created with samples taken from CLC (CORINE Land Cover) maps and LUCAS (Land Use and Coverage Area frame Survey) by Parente et al. (2021) [hereby referred to as the "Parente dataset"]. The 1km resolution HILDA+ dataset was used for the years 1984-1998, whereas the 30m resolution Parente dataset was used to derive data for the years 1999-2020. The HILDA+ dataset was reprojected in ArcGIS Pro to ETRS 1989 LAEA to match the projection of the Parente dataset. Binary annual forest cover maps were created from these two datasets, and points that experienced more than one switch in afforestation and deforestation were eliminated. The remaining points were grouped together into eight categories representing the type of forest cover change that occurred (i.e. afforestation or deforestation) and the time period that it occurred in (Table 1). Categories were made based on 15-year increments. This was in order to more accurately identify long-term changes to the landscape from the satellite imagery. The decision was made later to simplify the categories into four when creating the statistical models. This was done in order to improve model performance (see Analysis section).

Category Name	**Category Description**	**Simplified Category**
Forest_prew1985	Old growth since before 1985	Forested
Forest_prew2000	New growth between 1985 and 2000	Forested
Forest_prew2015	New growth between 2001 and 2015	Forested
Forest_post2015	New growth after 2015	Forested
Clear_prew1985	Unforested since before 1985	Cleared
Clear_prew2000	Deforestation between 1985 and 2000	Cleared
Clear_prew2015	Deforestation between 2001 and 2015	Cleared
Clear_post2015	Deforestation after 2015	Cleared

Table 1: The eight original forest-history categories created from the HILDA+ and Parente datasets.

In order to find suitable sites, focal statistics were run on the Parente dataset points. Using a radius of 550m, the percentage of area covered by the forest change type was calculated. The 550m radius was chosen as this reflects the average daily range for wild boar, which have been recorded as ranging between approximately 0.5km^2 (Johann et al. 2020) and 1 km^2 (Podgórski et al. 2013). The execution of the focal statistics resulted in a density map, which showed the areas where the categories were most prevalent by using a colour gradient. This step was not necessary for the HILDA+ dataset, as the 1km resolution of the dataset matches the defined parameters. Each of the resulting maps was combined with recent binary maps of landcover types from the Parente dataset in order to detect forest pixels that bordered onto pastures. A moving window approach was used to eliminate points that were located less than 1km away from major settlements and roads, as wild boar are more likely to root in areas that are less disturbed by humans (Theuerkauf & Rouys, 2008).

Sites were chosen from the upper quantiles of each category as much as possible in order to sample from areas where the type of forest change was most represented or intense. Where possible, sites were chosen to be as close to the category point as possible (ideally within a 500m radius), but sometimes were located further (but never more than a 1km radius). In places where multiple suitable pastures were present, pastures that were closer to the category point or had the least fragmented forest border were chosen in order to better represent the habitat of the boar. A maximum of one pasture per 1km radius was surveyed. All sites were located >1km apart from each other to prevent overlap between categories and to limit any possible double-sampling of damage created by the same group of boar.

In order to fulfil the site selection criteria, sites had to be classified as primarily grass fields. While some of the chosen fields had some mixed use (e.g. they had a couple of fruit trees), these were generally avoided during site selection in order to maintain consistency between sites. In addition to this, only fields with light or no fencing were chosen as sites. This was in order to make sure that any possible boar presence was not impeded by structures such as boar-proof fencing.

Sites were spread as evenly as possible throughout the study region and between the two countries. This was in order to create a balanced selection of sites, and to avoid any possible bias created from, for example, differing farming practices between the two countries. Despite these efforts however, more sites were selected in the Czech Republic than Slovakia due to easier communication with farmers and more up-to-date land ownership databases.

Permission to drone was obtained verbally from phone calls with the owners of the pastures. The contact details of owners were found in public agricultural databases (Land Parcel Identification System (LPIS) for the Czech Republic, and the aplikácii Geopriestorová žiadosť o podporu (Geospatial Support Request App) for Slovakia). Both privately-owned and cooperative-run pastures were selected for drone surveys. In cases of cooperative-owned fields, permission was obtained from the cooperative rather than the individual farmer of the field.

3.3. Drone Surveys

Droning took place during the autumn period of 2023 and 2024. In 2023, a Mavic S2 was used for the surveys, whereas a Phantom 4 RTK was also used in addition to the Mavic in 2024. Flights were pre-planned but were altered as needed in cases of unexpected obstacles (e.g. tall pylons in a field that were not shown on older satellite imagery). For each field, the date and time of the survey, the name of the farmer, the location coordinates, the name of the file, the size of the transect, and the land-use category were noted down. In addition to this, the presence of damage (if seen), as well as any other relevant observations (e.g. the presence of cattle damage, which may be confused for boar damage), was also taken note of. A total of 55 surveys were conducted in the summer of 2023, whereas 103 were conducted in October 2024.

Drones were flown at a height of 30m with an overlap of 80-84% (Mavic) and 70-80% (Phantom). The surveys covered a transect of a maximum of 100m in width (from the forest edge) and 250m in length. These measurements were dependent on the dimensions of the field; for smaller fields, this number was adjusted accordingly. Camera angles for both drones were positioned at 90 degrees. For both drones, the automatic camera settings were chosen in order to maximise success in case of changes in light or other environmental conditions. Surveys were conducted only during dry and calm weather. Images were digitally stitched together before analysis. A total of eight orthomosaics needed to be eliminated from the analysis due to issues with image quality.

Figure 1: Illustration of drone transect set-up, showing maximum dimensions

3.4. Analysis

3.4.1. Mapping

Figure 2: Images from surveys showing an example of boar rooting damage (top) and cattle damage (bottom). Cattle damage was discarded from field polygons during the mapping process.

The mapping of damage was conducted manually using ArcGIS Pro and a Wacom drawing tablet. For each orthomosaic, a polygon representing the visible portion of the field was mapped out by removing the tree line and other objects such as sheds, roads, tractors, and single trees. Areas that were deemed to be significantly blurred, distorted or dark were also not included in the field polygon. If present, the boar damage would also be mapped as a separate polygon. To maintain consistency, polygons were drawn with the orthomosaics zoomed to 1:1 scale. Boar damage was defined as uprooted soil or signs of digging (see Figure 2). Damage was mapped conservatively; if the damage was unclear, or if it was difficult to ascertain whether the damage was clearly created by boars or a different animal, the damage was not included in the damage polygon. In addition to this, areas that were significantly damaged by cattle were excluded from the field polygon in order to prevent accidental inclusion of possible boar damage into the field polygon. Two variables of damage were calculated: the absolute damage (in m^2) and the proportion of the visible field damaged (expressed as a decimal between 0 and 1). All mapping work was projected to the ETRS 1989 LAEA coordinate reference system.

3.4.2. Other variables

In addition to boar damage, the mean slope of the fields, the proportion of nearby current forest cover, and the proportion of nearby current human infrastructure were also calculated. Slope was calculated as it was hypothesised that steeper terrain may deter boars from rooting (Eshtiaghi et al., 2024). Slope data was obtained from the EU-DEM dataset, which is produced by the Copernicus Programme (Eurostat, n.d.). The proportion of human infrastructure was included as a variable in order to see whether increased infrastructure deterred damage. The proportion of human infrastructure was calculated by using the Parente dataset. A binary raster layer was created where human infrastructure variables were combined into one category, and the remaining variables were merged into a second category. The centroid of each field was found, and a 500m buffer was created around this point, reflecting again the average daily range of the boar. From this buffer, the proportion of human infrastructure was calculated using zonal statistics. Finally, current forest cover was calculated in order to explore whether greater cover decreased damage due to greater foraging potential in forests (as seen in Bobek et al., 2017). The proportion of current forest cover was calculated by using the same method used to calculate human infrastructure, specifically with the coniferous forest and deciduous forest variables from the Parente dataset. The data on damage, field sizes, mean slope, proportion of human infrastructure, and current forest cover were tabulated and exported to Excel. Exploratory statistics were conducted in Excel.

3.4.3. Modelling

Statistical modelling was conducted in R. During pre-processing, the continuous variables for slope, human infrastructure and current forest cover were standardised. Coordinates were also transformed to projected meters. A spatial autocorrelation test (Moran's I) was run in order to detect whether data points were significantly clustered. The results of Moran's I showed significant spatial autocorrelation. Upon closer inspection of the data, it was discovered that three pairs of fields were less than 1km apart from one another. Therefore, three fields were excluded in order to resolve this issue. Fields from categories with larger samples were chosen to be excluded over fields from less-represented categories. A fourth pair of fields was found to be 981m apart, but were not excluded as the distance was seen as reasonably within the margin of error. Removal of the three fields resulted in a total of 147 fields being used in the analysis. The removal of the fields did not improve the results of Moran's I, but the decision was maintained in order not to violate the assumptions of the study design.

Outliers were also investigated during pre-processing. Although Cook's distance identified several outliers in all models, further investigation revealed that none of these outliers combined high leverage and residual values. A sensitivity analysis confirmed that they did not distort any trends. All outliers were therefore kept in the analysis.

The data was modelled using generalised additive models (GAMs). GAMs were chosen due to their flexibility regarding non-linear relationships and their ability to include smoothing effects (splines) to continuous predictor variables (Wood, 2017). They also provide practical solutions to issues of spatial autocorrelation. Splines were therefore applied to the mean slope (which was strongly positively skewed) and to the spatial coordinates in order to counteract these issues. All models used seven predictor variables (Table 2).

<table>
<tr><th>Model Name</th><th>Dependent Variable</th><th>Predictor Variables</th></tr>
<tr><td>Binomial</td><td>Prescence of field (binary, TRUE/FALSE)</td><td rowspan="2">- Forest History Category
- Mean slope
- Proportion of human infrastructure</td></tr>
<tr><td>Gamma</td><td>Absolute damage (m^2) (continuous)</td></tr>
</table>

Beta regression	Proportion of field damaged (as a decimal between 0 and 1)	- Proportion of current forest cover - Year - Country - Coordinates (expressed in meters, projected to ETRS 1989 LAEA)

Table 2: List of dependent and predictor variables per model.

Three types of GAM models were constructed. The first was a binomial GAM model that predicted the probability of a field being damaged (hereby referred to as the "binomial model"). The second was a gamma GAM model that predicted the intensity or magnitude of damage per m^2 given that damage has already occurred (hereby referred to as the "gamma model"). Lastly, a beta regression GAM was conducted to predict the proportion of a field damaged by boar, given that damage has already occurred (hereby referred to as the "beta regression model").

All three models were initially programmed to use all eight forest history categories. However, given the small sample sizes per category, the decision was made to collapse the eight categories into four in order to avoid overparameterization. These final four categories are: forest pre-1985, forested post-1985, clear pre-1985, and cleared post-1985. Using simplified categories improved the performance of the original models by lowering their AIC by ≈1.5 – 8 points, and increased or roughly maintained their R^2 scores. Explained deviance only experienced a minor decrease in the simple models (3-6%). Due to the improvements in model fit after collapsing the categories, the decision was made to use the simplified forest history categories in the final models.

3.4.4. Spatial Analysis

In order to investigate the spatial distribution of predictions and to examine whether predictions had any spatial significance, spatial analysis was conducted in ArcGIS Pro. First, three separate kernel density maps were created using the predictions from each model in order to visualise the locations and predicted intensity of damage. The search radius was set to 3000m in order to reflect the mean closest distance between fields. The search radius was kept conservative in order to prevent over-smoothing. Natural breaks (Jenks) was chosen as the classification method, as this best suited the nonnormally distributed nature of the data. In addition to the kernel density maps, statistically significant hotspots of predicted boar damage were identified using the Getis-Ord Gi* statistic in ArcGIS Pro. A fixed band of 3000m was used in the calculations, again to reflect the mean closest distance between fields.

4. Results

4.1. Descriptive statistics

Following the elimination of unsuitable sites, a total of 147 fields were used in the analysis. Of these, 47.6% (*n* = 70) were classified as being damaged by wild boar, whereas 52.4% (*n* = 77) were undamaged. The majority (63.9%, *n* = 94) of all fields were located in the Czech Republic, of which 36.2% (*n* = 34) were damaged. The remaining 36.1% (*n* = 53) fields were located in Slovakia, of which 66.7% (*n* = 36) were damaged. Regarding the year of data collection, 36.7% (*n* = 54) of the sites were surveyed in 2023, whereas the majority of fields (63.3%, *n* = 93) were surveyed in 2024. Of the fields surveyed in 2023, 51.9% (*n* = 28) were damaged. In the 2024 cohort, 45.2% (*n* = 42) of the surveyed fields showed damage. Field transect sizes ranged from 2583.5m^2 to 36271.7m^2 (M = 14641.6, SD = 7745.5). The mean distance between surveyed fields that were closest to each other was 3127.5m.

Simplified Forest History Category	**Number of surveyed fields**	**Number of damaged fields**
Forest pre-1985	38	13
Forested post-1985	36	19
Clear pre-1985	18	8
Cleared post-1985	55	30

Table 3: Number of sites surveyed and the number of sites that were classified as damaged per simplified forest history category.

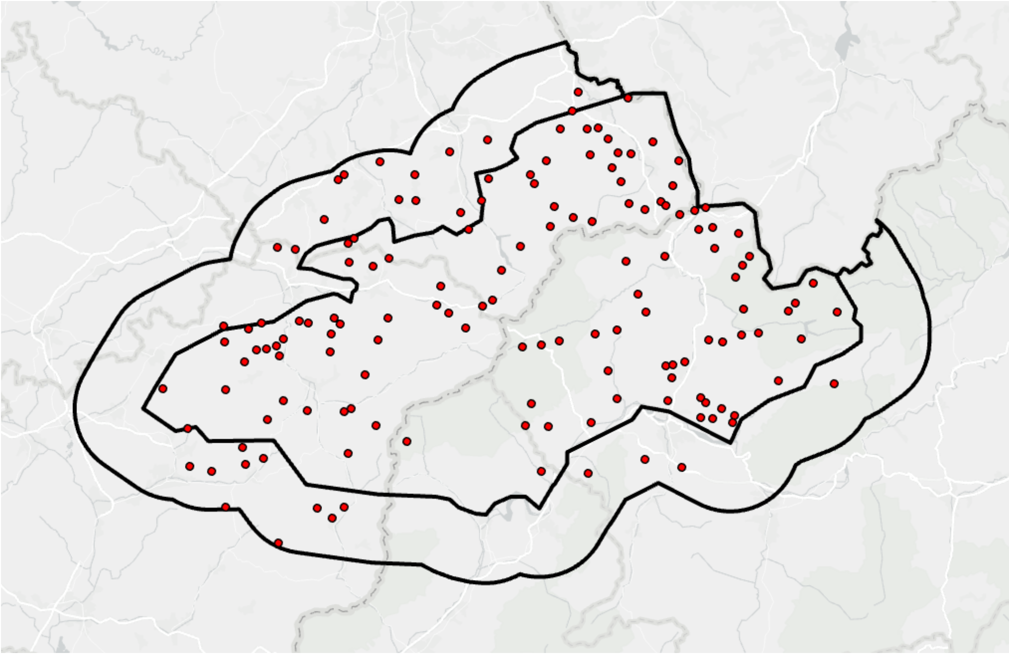

Figure 3: Map showing the study region outline in black and the surveyed fields in red. The dotted grey line represents the Czech-Slovak border

In damaged fields, the total damaged areas ranged from 1.0m^2 to 5930.6m^2 (*M* = 292.7, *SD* = 712.0). Translated to proportion of field transect damaged, this resulted in a range between < .001 and .3 (*M* = .04, *SD* = .05). When examined using the four simplified forest history categories, the mean absolute damage in damaged fields was highest in the cleared post-1985 category (*M* = 729.5, *SD* = 1213.2) and was lowest in the clear pre-1985 category (*M* = 352.1, *SD* = 477.0). For the proportion of field damaged, the forest pre-1985 category showed the highest mean (*M* = .05, *SD* = .06), while the clear pre-1985 category showed the lowest mean (*M* = .02, *SD* = .02).

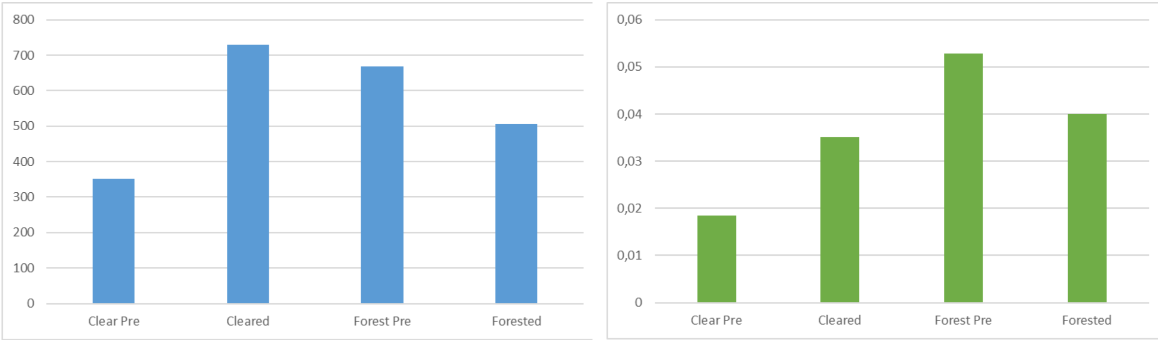

Figure 4: The mean absolute damage (in m^2) in damaged fields per forest history category (left) and the mean proportion of damage in damaged fields per forest history category (right).

The mean slope (in degrees) across all fields ranged from 0.1 to 12.1, with the overall mean slope being 3.1°. The distribution of the slope mean was positively skewed, with the majority of fields (62.6%, n = 92) experiencing a mean slope of less than 3.1°. Human infrastructure within a 500m radius was also positively skewed in distribution, with 83.7% (n = 123) of sites experiencing a proportion of coverage of less than .04 (M = .02, SD = .05). Current forest cover within a 500m radius was more normally distributed in comparison, and ranged between .06 and .89 (M = .5, SD = .2). Individual correlation tests were performed between the above three variables and the two types of dependent variable (absolute damage and proportion of damage), but only showed very weak or non-existent insignificant relationships.

4.2. Binomial Model (presence/ absence of damage)

A GAM using a binomial distribution and a logit link function was used to examine the probability of fields being damaged by wild boar. For the forest history categories, forest pre-1985 was used as the reference level. The model explained 12.7% of deviance (adjusted R^2 = 0.10), which was the lowest amount of deviance explained among the three models. None of the parametric or the smooth terms were significant predictors at a .05 significance level. A weak, insignificant positive trend was observed with the predictor country- Slovakia (β = 1.16, SE = 0.74, z = 1.58, p = .117). Out of the two smooth terms, the spatial term (x meters, y meters) approached significance with a positive trend ($X^2(2)$ = 5.29, p = .068).

4.3. Gamma Model (absolute damage)

A GAM with a gamma distribution and a log link function was created to predict the effect of the parametric and smooth variables on absolute damage (in m^2) to a field, given that the field is damaged. For the forest history categories, forest pre-1985 was used as the reference level. The model explained 22.4% of the deviance (adjusted R^2 = 0.05), which was the highest explained deviance result across the three models. Of the parametric terms, current forest cover (β = 0.61, *SE* = 0.2, *t* = 3.08, p = .003) and forest post-1985 (β = -1.09, *SE* = 0.49, *t* = -2.24, *p* = .029) were identified as significant predictors to absolute damage, where current cover was identified as having a positive effect and forest post-1985 was seen to have a negative effect. A weak positive, but not significant trend was created by human infrastructure (β = 0.2, *SE* = 0.14, *t* = 1.39, *p* = .170). Neither of the smooth terms was a significant predictor in the gamma model, although the spatial term was close to being significant with a positive trend (*F* = 3.12, *p* = .052).

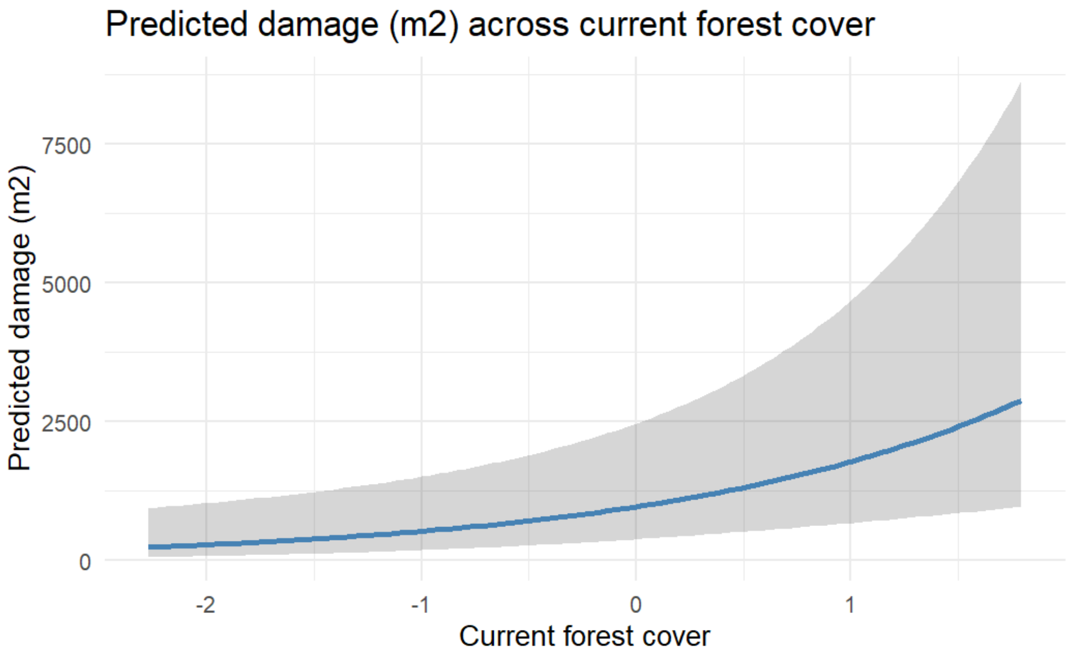

Figure 5: Plot showing a significant positive trend between predicted damage (m^2) in damaged fields and current forest cover.

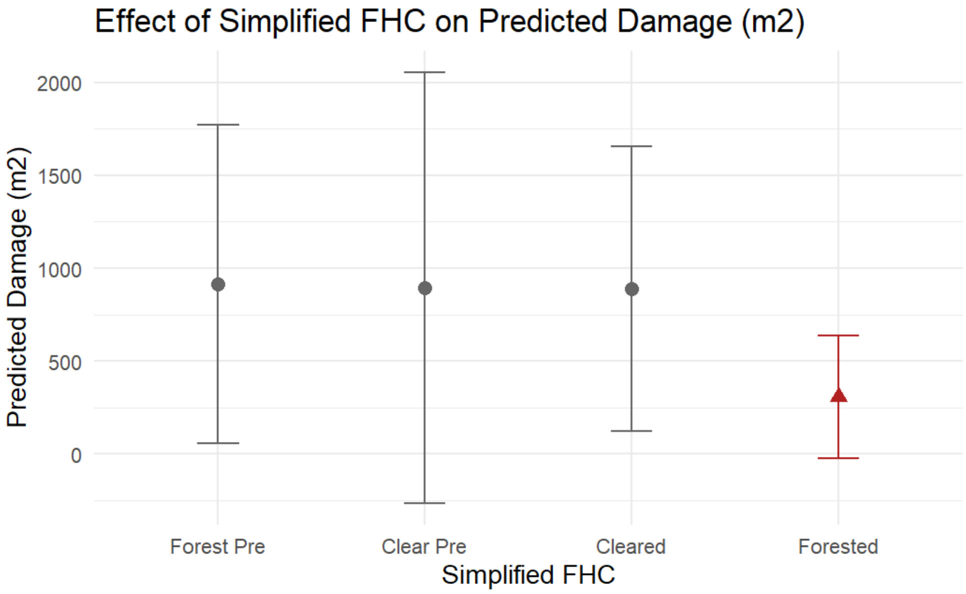

Figure 6: Plot showing predicted damage in m2 (±95% CI) across the four simplified forest history categories, from the gamma GAM with covariates held constant. Forested post-1985 sites show significantly lower predicted damage.

4.4. Beta Regression Model (proportion of damage)

The third GAM used a beta distribution and a logit link function to predict the proportion of a field damaged, given that damage has already occurred. For the forest history categories, forest pre-1985 was used as the reference level. The model explained 14.2% of the deviance (adjusted R^2 = -0.01). Of the parametric terms, human infrastructure was found to be a positive predictor of the proportion of field damaged (β = 0.21, *SE* = 0.09, *z* = 2.40, *p* = .016). Current forest cover also produced a positive but not significant trend (β = 0.26, *SE* = 0.16, *z* = 1.75, *p* = .080). No notable trends were observed amongst the smooth terms.

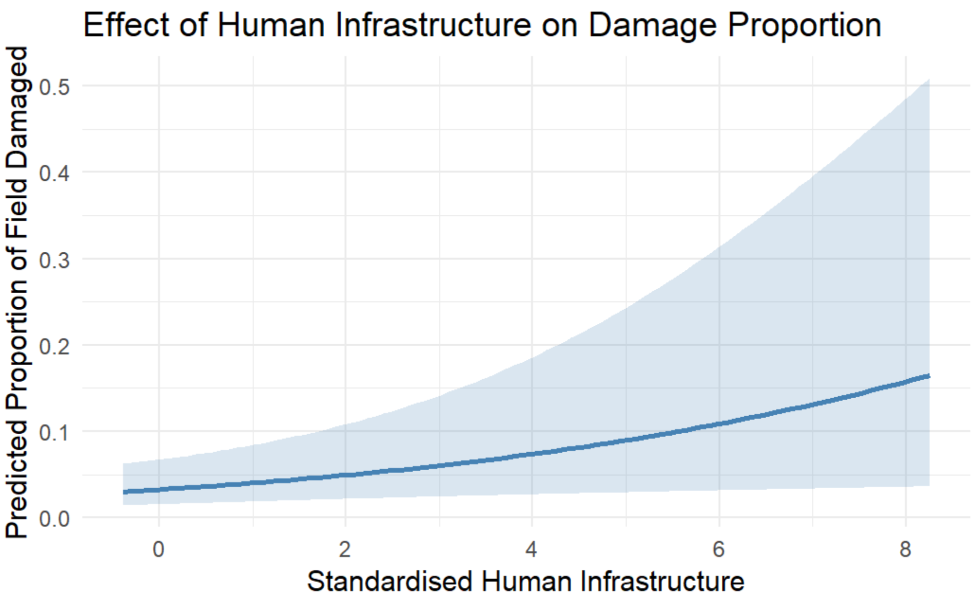

Figure 7: Plot showing a significant positive influence of human infrastructure and the predicted proportion of damage to damaged fields.

4.5. Spatial Analysis

Three kernel density maps were created using the predictions generated by each model (Figure 8). The dark red spots indicate areas where predicted damage is concentrated relative to other areas. All three maps show that the highest concentrations of damage prediction values are located in the southeast of the study region.

The results of the Getis-Ord Gi* calculations display significant hotspots and cold spots in the study region. Hotspots indicate areas where high damage prediction values are significantly clustered, whereas cold spots are produced from significant clusters of low values. From the predictions created by the binomial model, the Getis-Ord Gi* tool identified eight hotspots and five cold spots within a 95% CI. Three hotspots were identified from the gamma model, whereas three cold spots were identified using the beta model predictions (all within a 95% CI). Most of the hotspots are generally located on the southern side of the study region, whereas cold spots are observed primarily on the northern side. Almost all hotspots (*n*= 10) from the models combined are located in Slovakia, whereas all the cold spots are located in the Czech Republic.

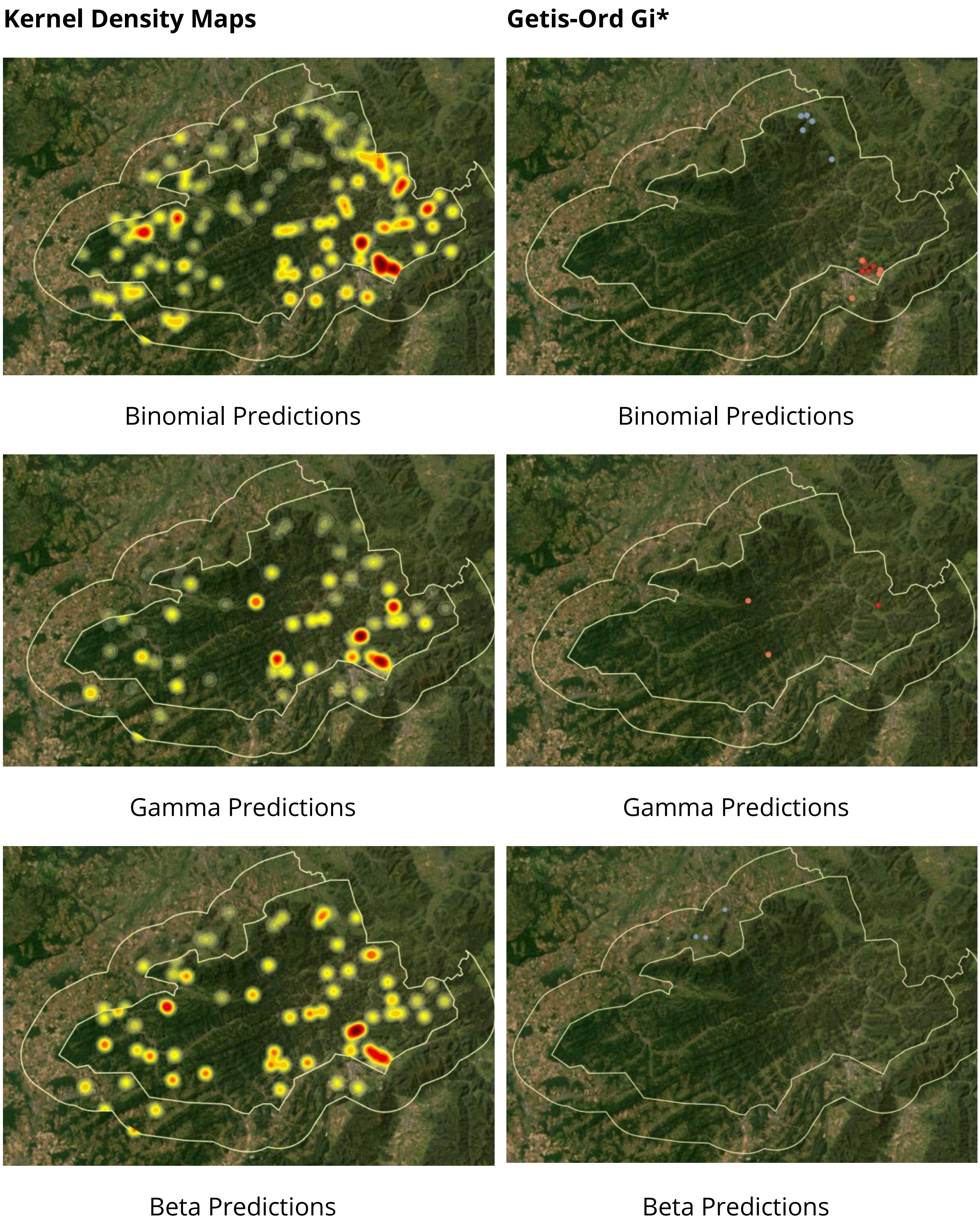

Figure 8: Kernel density maps (in left column) and heatmaps created from Getis-Ord Gi statistics tool (right column) using the prediction from the three models. For the Getis-Ord Gi*maps, the blue spots represent significant coldspots within a 95%CI, the orange spots represent significant hotspots within a 95%CI, whereas red spots represent significant hotspots within a 99%CI.*

5. Discussion

5.1. Interpretation of results

The results indicate that there were differences in damage levels to fields when investigated using the four forest history categories. However, when models were used to analyse what best predicts boar damage, forest history was only significant in the gamma model. The gamma model indicated that the category forested post-1985 had a significant negative effect on absolute damage. This indicated that predicted damage was significantly lower in fields that belonged to the younger forest category compared to fields that belonged to the older forest category.

This finding partially supports the hypothesis stated in the introduction, which expected higher levels of predicted damage in fields that belonged to the older forested category. Higher levels of damage were expected in forested categories, especially older forests, due to the findings of previous literature, which discovered more intense damage in older forests due to higher food and shelter availability (Drimaj et al., 2025, Haaverstad et al. (2013). Younger forests may not be as attractive to boar due to less food and inadequate shelter opportunities. Therefore, the appeal of older forests for boar may explain a greater abundance of boar in these areas compared to younger forests, which may lead to increased damage to neighbouring fields.

However, the initial hypothesis expected significantly lower predicted values for damage in fields that belonged to the two deforested categories (clear pre-1985 and cleared post-1985). This was not seen in any of the model results. This may be due to the very adaptable nature of wild boar (Faltusová et al., 2024), which may make them somewhat resilient to changes caused by past and recent deforestation. In addition to this, the effects of more significant variables, such as current forest cover, may have masked any changes or overridden any potential effects caused by deforestation.

Current forest cover was found to be a significant predictor for absolute damage in the gamma model, and it created a positive but not significant trend in the beta model. Previous literature has found that boars prefer larger forest islands over small ones in fragmented or mosaic landscapes (Virgós, 2002) and that they stay close to forest edges when entering fields (Thurfjell et al., 2009). Higher levels of forest cover around a field may provide boars with a sense of security when entering a field, compared to more sparsely covered or exposed localities. This sense of security may therefore make boars more likely to root in fields with higher levels of nearby forest cover compared to areas with lower cover.

Contrary to expectation, human infrastructure was also found to be a significant positive predictor of proportional damage in the beta model. It also produced a positive, but not significant effect in the gamma model. Although many previous studies have found that boar damage to farmland decreases with increased urbanisation (e.g. Cappa et al., 2019), there is also evidence that boars can be very tolerant of humans compared to other ungulates, especially those that live in urban areas (Stillfried et al., 2017). One study by Rutten et al. (2019) also showed increased likelihood of damage occurring near urban areas, although the authors believe this to be due to model unreliability rather than a natural phenomenon. Although this may indeed be the case for the models used in this research, their results should not be immediately dismissed, especially taking into account the aforementioned adaptable and tolerant nature of wild boar.

The other notable, but not significant, trends produced by the models are also worth mentioning. Positive trends were seen in both the binomial and gamma models for the spatial term. This is not surprising considering the results of the spatial analysis, which showed significant clustering of damage. The term Slovakia from the country variable also indicated a positive trend in the binomial model, suggesting higher chances of damage occurring in Slovakia than Czech Republic. Since the percentage of damaged fields was higher in Slovakia than in the Czech Republic, this trend is not unexpected. However, the sample size for Slovakia was much smaller than for the Czech Republic, so the trend may not exist if the sample sizes were more equal.

It is also important to note the lack of effects seen from several variables in the models. The term Year did not produce any notable trends, even though there was anecdotal evidence from farmers that suggested that damages were more severe in 2023 than in 2024. However, these may have been localised effects that were not relevant when looked at on a wider geographical scale. Slope also did not produce any noteworthy results, even though it was expected that boars would prefer smoother fields than steep ones. The smoothening spline used in the GAMs for the slope term may have over-smoothened the data, although this is not certain. The effects and strength of the smoothing spline should be further examined in future models.

The results of the spatial analysis reveal interesting patterns of spatial clustering, especially in the southern part of the study region, where numerous significant hotspots are located. Further inspection of these southern hotspots indicates a larger general cluster near the city of Žilina in Slovakia. Although this cluster may seem initially surprising due to the heavy levels of urbanisation around Žilina, it may be explained by the presence of a nearby national park (Malá Fatra). The border of Malá Fatra's buffer zone is located mere kilometres from Žilina. The spillover effect created by the national park, where hunting is banned, may explain the higher abundance of boar, and therefore higher levels of damage. This effect was also observed by Amici et al. (2011), who use the term "refuge effect" to describe the nurturing effect that hunting-free buffer zones have on boar populations and subsequent damage to agriculture.

In addition to hotspots, numerous cold spots were also identified during the spatial analysis, the majority of which were located on the northern side of the study region. Examination of boar hunting data from 2016 (Turek et al., 2018) reveals that the cold spots align with areas where fewer boars were caught, possibly indicating lower boar abundance levels in these regions. Rough visual inspection of satellite imagery also shows that these cold spots appear to be in more agriculturally-intensive or relatively fragmented landscapes, which may or may not explain this lack of abundance.

5.2. Limitations and future research

There are a few constraints to this research that should be mentioned. A critical look at the study design shows that the sample sizes were imbalanced, with substantial variation between the sample sizes per forest history category, year, and country. This imbalance was partially due to data availability: for example, certain categories were more abundant in the study region than others. Even though the data was checked for extremely influential outliers, the imbalance may still have skewed the results in categories with fewer samples.

Another factor that may have masked some results is the decision to simplify the forest history categories. Although the simplification improved the performance of the models, nuance in the results may have been lost due to this. Future modelling, given a more balanced dataset, could examine the differences in more detail with more forest history categories.

Although model performance was improved by the simplification of the forest history categories, their predictive power could still have been strengthened with some critical analysis of the existing variables. Other variables that may have been relevant should also be explored in future studies; for example, the soil type of fields may have an effect on damage, as it is known that boars prefer to root in certain soils over others (Laznik & Trdan, 2014). It is also possible that other model types could fit the data and research questions more appropriately. Future research could therefore develop more robust models for this research topic by exploring the potential effects of other variables, as well as experimenting with different types of statistical models.

Finally, the integration of boar population data could really complement the findings of this research, especially when combined with the insights highlighted by the spatial analysis. Including population dynamics could help us understand if boar damage patterns are simply linked to boar abundance and/or density, or if the damage is also explained by other factors. By linking population data and spatial analysis, deeper insights could be gained into the nature of hot and cold spots, as well as the part played by refuges such as national parks and buffers. The results of this synthesis could give a more thorough overview of boar damage patterns that may be useful to certain stakeholders in the region, such as wildlife management authorities, local governments, and farmers. In addition to this, the impact of this research could be furthered in future studies by working in collaboration with such stakeholders to enrich the scope and relevance of these findings.

6. Conclusion

As rural land abandonment continues and populations of large mammals such as wild boar increase in Europe, more research is needed into the relationships between these ungulates and the landscapes that they inhabit. Understanding the drivers of wild boar damage in certain regions may not only aid wildlife management services and farmers, but could help nurture human-wildlife coexistence in areas where conflict caused by agricultural damage is severe. By analysing whether damage probability and intensity can be predicted by landscape-level variables, this research illustrated that certain factors, such as forest history, current forest cover, and proportion of human infrastructure, can influence patterns of boar damage. In addition to this, spatial analysis revealed significant clusters of predicted damage in certain areas of the study region. Future research should analyse if the results are connected to boar population dynamics and should investigate the potential effects of other variables, such as soil type. In addition to this, future studies could further the scope of this research by broadening the methodology to include social scientific methods in collaboration with relevant stakeholders, including farmers.

7. Generative AI Statement

Generative AI tools (namely ChatGPT and Consensus) were used during this research. ChatGPT was used for brainstorming ideas and checking coding errors, whereas Consensus was used during the literature review process to gain overviews of existing research gaps. All work in this report has been solely produced by the author, unless otherwise stated. No work in this report has been generated by AI machines.

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10. Appendix

Model Tables

10.1. Binomial GAM

Binomial GAM - Parametric Terms

Term	estimate	std.error	Z value	p.value
Intercept	-0.625	0.596	-1.049	0.294
Infrastructure	-0.258	0.218	-1.181	0.237
Year- 2024	-0.288	0.407	-0.707	0.480
Country- SK	1.160	0.740	1.568	0.117
Current forest cover	-0.139	0.245	-0.568	0.570
Simplified FHC Clear Pre 1985	-0.093	0.775	-0.120	0.904
Simplified FHC Cleared Post 1985	0.620	0.519	1.194	0.232
Simplified FHC Forested post 1985	0.201	0.567	0.355	0.722

Binomial GAM - Smooth Terms

Term	edf	ref.df	Chi.sq	p.value
s(Slope_mean)	1	1	1.949	0.163
s(x_meters,y_meters)	2	2	5.388	0.068

10.2. Gamma GAM

Gamma GAM - Parametric Terms

Term	estimate	std.error	T value	p.value
Intercept	6.214	0.625	9.948	0.000
Infrastructure	0.197	0.142	1.390	0.170
Year- 2024	0.230	0.312	0.737	0.464

Term	estimate	std.error	T value	p.value
Country- SK	0.276	0.665	0.416	0.679
Current forest cover	0.606	0.197	3.080	0.003
Simplified FHC Clear Pre 1985	-0.023	0.665	-0.035	0.973
Simplified FHC Cleared post 1985	-0.027	0.425	-0.063	0.950
Simplified FHC Forested post 1985	-1.089	0.485	-2.243	0.029

Gamma GAM - Smooth Terms

Term	edf	ref.df	F	p.value
s(Slope_mean)	1.874	2.264	1.948	0.173
s(x_meters,y_meters)	2.001	2.002	3.117	0.052

10.3. Beta GAM

Beta GAM - Parametric Terms

Term	estimate	std.error	Z value	p.value
Intercept	-3.364	0.498	-6.753	0.000
Infrastructure	0.213	0.089	2.401	0.016
Year - 2024	-0.032	0.249	-0.130	0.897
Country - SK	0.201	0.523	0.384	0.701
Current forest cover	0.275	0.157	1.751	0.080
Simplified FHC Clear Pre 1985	0.180	0.537	0.335	0.737
Simplified FHC Cleared post 1985	0.189	0.338	0.559	0.576
Simplified FHC Forested post 1985	-0.020	0.385	-0.053	0.958

Beta GAM - Smooth Terms

Term	edf	ref.df	Chi. sq	p.value
s(Slope_mean)	1.325	1.571	0.206	0.827
s(x_meters,y_meters)	2.000	2.001	0.614	0.736