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Human–wildlife impacts (HWI) occur due to interactions between wildlife and human activities in our increasingly anthropogenic world and typically result in economic losses or increased health- and safety risks. HWI can be especially prevalent where urbanization encroaches upon natural areas, or in fragmented human-dominated landscapes. An example of such situation is the re-occurrence of wild boar in Flanders (northern Belgium). Flanders is one of the most densely populated areas of Europe and is characterized by a severely fragmented landscape. The recent return of wild boar to Flanders challenges managers to find solutions for a sustainable co-existence between humans and wild boar. As crop damage is increasing and targeting preventive measures efficient requires identifying high risk areas, we assessed the influence of the landscape around a field, as well as field-specific characteristics on the likelihood of wild boar crop damage. Because most of the reported damage in Flanders occurs in grasslands (cultivated to produce hay) and maize fields, we focused on these. We used boosted regression trees and the brglm-technique to construct distribution models explaining spatial patterns of crop damage. We found that for maize fields, landscape-level variables such as the proportion of maize, grassland, forest and urbanized areas in the surroundings of the field are key factors determining the probability of damage. In contrast, field-specific variables only played a minor role. For grasslands, both field-specific and landscape characteristics affected damage probability: a higher probability of damage was associated with decreasing distance to nearest forest, increasing distance to the nearest road, the use of inorganic fertilization and increasing age of the grassland. Our results suggest that the risk of crop damage by wild boar can potentially be mitigated by changes in agricultural practices that alter grassland characteristics, and by targeting preventive measures towards high risk maize in well-defined locations.

Key words: crop risk assessment, damage probability, landscape fragmentation, risk assessment, species distribution modeling, *Sus scrofa*

The growth of the human population and increasing human-dominated land use challenges many wildlife species' survival (McKee et al. 2004). At the same time, there are wildlife species which show increasing numbers due to protection or due to adjustment towards anthropogenic pressures or even benefit from urbanized areas through behavioral adaptations (Luniak 2004, Bateman and Fleming 2012, Lowry et al. 2013). Moreover, landscapes become increasingly anthropogenic and fragmented which causes wildlife to come more and more into contact with human activities (Messmer 2000, Barua et al. 2013). Human–wildlife impacts (HWI, here defined according to Redpath et al. (2013) as the impacts due to the interactions between wildlife and humans or their activities) often involve an economic component. This economic component is often one of the main limiting factors in acceptance of stakeholders for wildlife (Carpenter et al. 2013). A better understanding of how, where and why HWI emerge is essential for wildlife managers to find viable solutions and thus decrease negative impacts and increase stakeholder acceptance of wildlife (Messmer 2009, Young et al. 2010). Incorporating animal ecology in a multidisciplinary approach of wildlife management can be valuable towards the search for such solutions in HWI (Fryxell et al. 2014).

Wild boar *Sus scrofa* (L.) is a suid native to Eurasia. Wild boar increasingly cause HWI (Massei et al. 2015) as since the 1960s, populations throughout Europe and in other parts of the world where feral pigs have become an invasive alien species, started expanding (Saez-Royuela and Telleria 1986, Massei et al. 2015, Mayer 2018, Salvador and Fernandez 2018). Wild boar has become one of the most widespread

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mammals in the world (Keuling et al. 2018). More than half a century ago, wild boar disappeared in Flanders (northern Belgium) due to overhunting. Wild boar re-appeared in 2006 in the eastern province of Limburg in two geographically distinct locations. These founder populations were geographically not connected to existing populations, excluding natural recolonization by migration; however there is no confirmed information on the origin of these founder populations. Wild boar in Flanders is regarded as a native game species and the objectives for wild boar management are since 2016 set by stakeholder consultations for each out of 10 management zones (no presence allowed, zero acceptance of damage, limited damage as well as local populations allowed, but no further population increase). The current wild boar population in Flanders is still characterized by increasing population numbers and an expanding distribution range (Scheppers et al. 2014).

As Flanders is one of the most densely populated areas of Europe (Linnell et al. 2001, FOD Economie 2011), characterized by a severely fragmented landscape, wild boar presence results in increasing incidence of HWI. HWI involving wild boar can include disease transmission, traffic collisions and damage to agricultural crops (Bieber and Ruf 2005, Treves et al. 2006, Morelle et al. 2016). Especially damage to agricultural land is a growing concern because of the high economic impact for individual farmers. Annually reported damage to crops ranges from hundred thousand euros in the Netherlands to more than twenty million euros in France (Carnis and Facchini 2012, Faunafonds 2014). In Flanders, the extent of crop damage from wild boar is largely unknown as there is no standardized monitoring method (Rutten et al. 2018). This lack of data does not allow to assess the actual extent nor the potential extent of crop damage with future wild boar expansion. As these data are an essential aspect in a risk assessment involving stakeholder acceptance, we urgently need better insights into what attracts wild boar to specific fields or grasslands where they cause damage (Rutten et al. 2019).

To obtain spatially explicit predictions of wild boar damage risk across Flanders, we applied species distribution modeling (SDM). SDM tools are widely used to gain ecological insights into a species distribution and make predictions of a species' (potential) distribution across landscapes (Jiménez-Valverde and Lobo 2007, Elith and Leathwick 2009). SDM are frequently applied as risk assessment tools (Jiménez-Valverde et al. 2011, Mateo-Tomás et al. 2012, Acevedo et al. 2014). SDM methods can not only be used to predict the distribution of the species itself (e.g. for wild boar, Saito et al. 2012, Morelle et al. 2016), but also to model the distribution of a species' impact, such as crop damage by wildlife (Tourenq et al. 2001, Sitati et al. 2005). For wild boar, SDM-approaches have been used to predict damages to croplands in a rice-paddies dominated region in Japan by Saito et al. (2011) and in southern Italy by Ficetola et al. (2014). One of the central assumptions of SDM are that training data (i.e. the input data used to calibrate the model) are representative of the environmental conditions of the regions for which predictions are made (Elith et al. 2010). Therefore, we aimed to construct an SDM explaining crop damage patterns by wild boar based on data collected in the severely fragmented landscape of Flanders itself. Farmers reporting damage indicate they have the impression that field-specific factors like fertilization and the previous cultivated crop on a field can be key factors explaining differences in damage probability between neighboring fields. Therefore, we did not only incorporate landscape variables but also field-specific factors that can be related to agricultural practices (i.e. fertilization, previous cultivated crop, etc.). Finally, as wild boar can show a substantial plasticity in adjusting to human-dominated environments (Stillfried et al. 2017), the Flemish landscape provides an interesting case study on damage patterns by wild boar in highly anthropogenic areas. Combining both landscape and field-specific aspects in a SDM we aim to answer following questions:

– Which factors in the landscape attract wild boar to a specific field in a highly anthropogenic area?
– Does landscape fragmentation affect damage patterns?
– Do field-specific factors have an extra explanatory power additional to landscape factors?

This study aims to increase our understanding about the characteristics of agricultural fields that are most likely to be damaged when wild boar are present based on landscape characteristics, with the ultimate goal to generate region-wide predictive crop damage risk maps. Moreover, a better understanding on field-specific characteristics allows to construct scenarios highlighting how relevant field-specific variables can modify landscape-related risks on crop damage.

Methods

Study area

Our study area encompasses the Flanders region of northern Belgium. Flanders has a surface of 13 587 km² and has a cool temperate and moist climate (Metzger et al. 2013) with an annual average temperature of 9.7°C and 800 mm rainfall. Flanders has mainly a flat or gently undulating landscape from sea level in the west to 150 m above sea level in the south and east. The Flemish landscape is highly fragmented with only 11% forests, 53% agricultural land, 30% built-up areas and the remaining 6% consists of water, swamps, heathlands, natural grasslands, estuaries and dunes (Demolder et al. 2014). An intense intertwinement of natural, agricultural and urbanized areas is crossed by a dense road network (5.08 km km⁻², Vercayie and Herremans 2015). The current distribution area of wild boar is mainly limited to the eastern provinces of Limburg, Antwerp and Flemish Brabant but their distribution range is expanding towards the center of the region (Fig. 1). We selected a study area of approximately 1000 km² in the province of Limburg (Fig. 1) where farmers often reported damage in an earlier survey (Rutten et al. 2019).

Data collection

Farmers and hunters were contacted through the local farmers- and hunters-organizations and were asked to report damaged fields by phone between June 2015 and September 2018. Rooting damage, damage due to feeding, wallow-
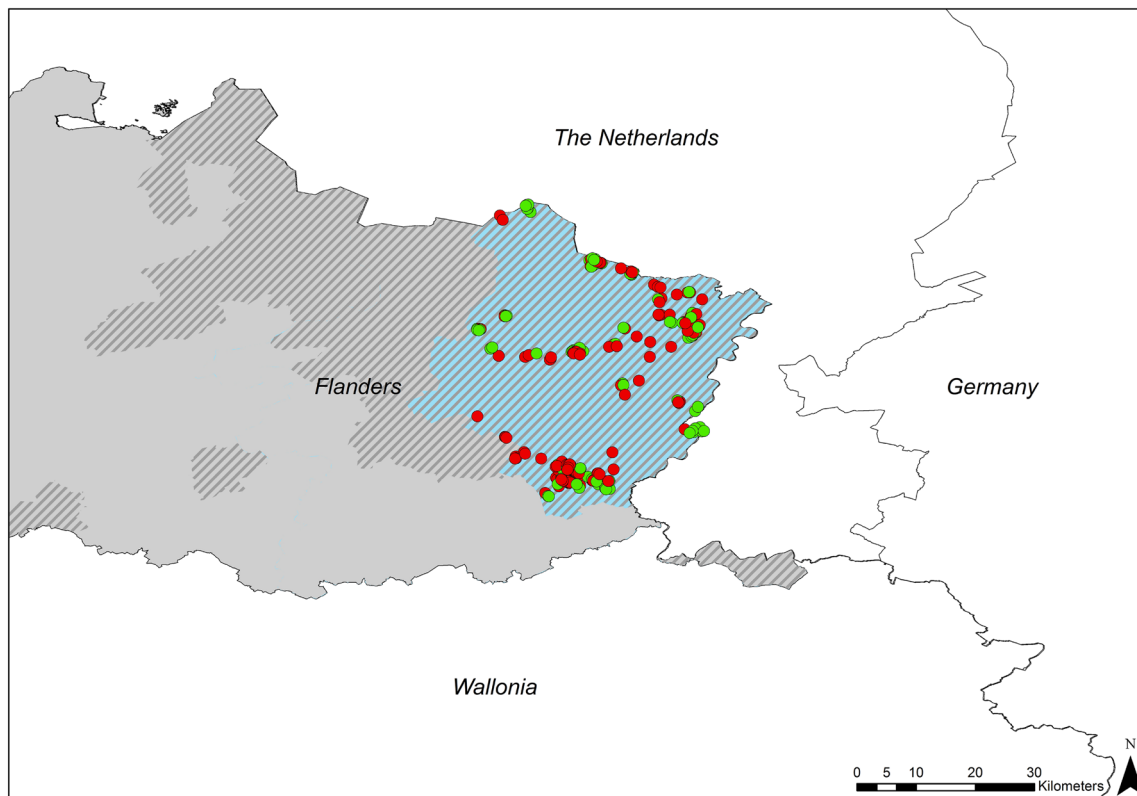
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Figure 1. Study area (blue) in the eastern province of Limburg of Flanders in which reported damaged crop fields by wild boar are recorded. The dashed area is the current wild boar distribution area (based on hunting bag statistics of 2018), dots indicate locations of fields for which data were collected, the green represent undamaged fields, de red dots damaged fields.

ing or damage after sowing of all possible crops (including grasslands which are further also classified as an agricultural crop) could be reported. During a field visit, we assessed if the field was indeed damaged by wild boar and the amount of damage was recorded during the field visit using a drone (Rutten et al. 2018). We considered a field to be damaged when damage was clearly visible, small intrusions were not included. For the purpose of this study, the information on the amount of damage was however not used as we used a binary classification: damaged or not damaged. Field-specific characteristics were recorded (crop type, fertilization type, variety in case of maize field, age in case of grassland). During the field visit, the farmer or hunter was also asked to point out an undamaged field of the same crop, within 500 m from the damaged field. After controlling that this second field was indeed undamaged using a drone, the same information on field-specific characteristics was recorded as for damaged fields. The set of undamaged fields acts as a control group in this study, resulting in a presence–absence dataset to test landscape and field-specific factors. In the end, only maize fields and grasslands were included in this study since we only received five reports of other crops being damaged by wild boar. In total, 275 fields were recorded between 2015 and 2018 (Fig. 1, Table 1).

Landscape variables

To identify landscape elements that influence wild boar crop damage patterns, we used a set of 15 landscape variables, which were selected based on the current knowledge of wild boar biology in literature (Table 2). These variables were calculated for each field of which data were collected during this study as well as for all fields in Flanders. This allowed us to make projections on crop damage probability for the rest of Flanders (Table 2). These calculations were done using the yearly Flemish parcel registration maps (EPR, from 2015 until 2017 (EPR of 2018 was not yet available, therefore the mean percentages from 2015 until 2017 were used for damaged fields of 2018), Flemish Land Agency), the land use map of Flanders (NARA level 1, Poelmans and Van Daele 2014) and the map of hunting grounds in which hunting rights are provided in Flanders (ANB, Agency for Nature of Forest). All calculations were conducted in ArcMap (ver. 10.4.1, ESRI Inc.). A buffer zone was drawn around each field with a width of 1.25 km which was used to calculate area-related variables (Table 2). This radius of 1.25 km results in a buffer area of at least 5 km² which corresponds to wild boar home ranges in

Table 1. Number of included damaged fields and undamaged fields per crop and per year.

	2015	2016	2017	2018	Total
Grasslands	5	54	22	9	90
Undamaged	2	13	6	7	28
Damaged	3	41	16	2	62
Maize fields	39	70	46	30	185
Undamaged	9	29	13	22	73
Damaged	30	41	33	8	112
Total	44	124	68	39	275

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Table 2. Landscape variables calculated for the observed damaged and undamaged fields in the collected dataset and for all fields in Flanders with both mean and standard error. To calculate road density, the total length of primary and secondary roads were divided by the buffer area. Habitat patch density was calculated as the number of habitat patches divided by the buffer area and mean habitat patch size in each buffer.

Variable	Study area	Flanders	Literature
Percentage of field edge which is forest	25.07 ± 2.63	5.41 ± 0.024	Briedermann 1990, Ficetola et al. 2014, Lombardini et al. 2016
Distance from field until nearest forest (m)	52.62 ± 6.74	163.02 ± 0.26	
Percentage of forest in buffer	23.29 ± 0.96	7.00 ± 0.013	
Percentage of low natural cover in buffer	2.04 ± 0.13	1.25 ± 0.0030	Thurfjell et al. 2009
Percentage of agriculture in buffer	51.07 ± 1.20	62.43 ± 0.026	Bleier et al. 2012
Percentage of maize in buffer	16.13 ± 0.59	15.80 ± 0.011	
Percentage of grasslands in buffer	19.46 ± 0.53	19.75 ± 0.015	
Percentage of urbanized area in buffer	17.71 ± 0.70	25.52 ± 0.018	Podgórski et al. 2013
Distance from field until nearest urbanized area (m)	48.46 ± 5.22	18.41 ± 0.071	
Road density (length of roads divided by buffer area)	3.43 ± 0.16	5.67 ± 0.0049	/
Distance from field until nearest road (m)	610.08 ± 34.48	394.17 ± 0.56	
Habitat Patch Density in buffer	9.63 ± 0.25	7.47 ± 0.0080	
Mean habitat patch size in buffer (km^2)	0.034 ± 0.0022	0.012 ± 0.000036	
Percentage of hunted area in buffer	85.56 ± 1.16	94.12 ± 0.018	Geisser and Reyer 2004, Keuling et al. 2008
Distance from field until nearest hunting area (m)	11.48 ± 4.06	9.98 ± 0.16	

Wallonia (southern Belgium), that ranges between $4.9\,km^2$ ($\pm 5.6\,km^2$) for males and $2.5\,km^2$ ($\pm 3.74\,km^2$) for females and juveniles (Prévot and Licoppe 2013). Fragmentation variables including habitat were calculated considering forest together with scrub and other low natural cover as wild boar suitable habitat.

Field-specific variables

For each reported agricultural field, field-specific variables were collected during the field visits (Table 3). Fertilizer application was subdivided into two separate variables: organic and inorganic fertilizer use. For maize fields, the specific variety was characterized using the precocity-value (FAO-value from the Food and Agricultural Organization) defining the timing of ripening of the variety. For grasslands, the age of grasslands was recorded (grasslands older than five years are considered permanent grasslands). As farmers had the impression that remains of maize from the previous year are rooted up by wild boar in grasslands, a binary variable representing the crop of the previous year (maize or no maize (i.e. grass, cereals, potatoes or nothing)) was included.

Distribution models

Variables were screened for multicollinearity using the Pearson's correlation coefficient (R-value) with $R = 0.7$ as a threshold to remove correlated variables (Dormann et al. 2013). Variables which showed multicollinearity with the largest number of other variables were removed step by step until none of the remaining variables showed a $R > 0.7$.

Models were constructed separately for maize fields and grasslands. For each crop, three models were built: a landscape model including only landscape variables, a field-specific model including only field-specific factors and a combined model that included all variables marked as relevant predictors of wild boar damage by the best landscape and best field-specific model.

We used Boosted regression trees (BRT) in R (<www.r-project.org>) as SDM algorithm as they typically have a high predictive performance, do not have a need for prior data transformations or for elimination of outliers, automatically incorporate interaction effects and are able to fit nonlinear relationships (Elith et al. 2008). We used the dismo R-package (ver. 1.1-4, Hijmans et al. 2017) to develop the BRT models. For BRT-modeling, optimal parameter settings

Table 3. Field-specific variables collected for the observed damaged and undamaged maize fields and grasslands by wild boar in the study area in Flanders with their categories or with its mean and standard error. The precocity-value defines the timing of ripening of the variety.

Maize fields	Dataset	Grasslands	Dataset
Organic fertilization (categories)	yes/no	organic fertilization (categories)	yes/no
Inorganic fertilization (categories)	yes/no	inorganic fertilization (categories)	yes/no
Precocity-value	243 ± 54	age	1–5 years or permanent
		crop of previous year (categories)	maize/no maize

(learning rate (lr), tree complexity (tc) and bag fraction (bf)) were first determined. To define optimal settings, the model was run with a range of possible settings of lr, tc and bf, averaging model outputs over 10 iterations to minimize variability between runs. Optimal settings were selected based on a minimum model output of 1000 trees and a minimal predicted deviance. Once the optimal settings were derived, the least important variables were removed by refitting the model each time with the removal of one variable while assessing the change in predictive deviance according to the procedure of Elith et al. (2008). The final model is obtained when the change in predictive deviance exceeds the original standard error of the full model (Elith et al. 2008). Additionally, the AUC-value (area under the receiver-operating characteristics curve or roc-curve) of the final model was calculated; AUC-values vary between 0 and 1 with values higher than 0.5 reflecting a better ability for a model to discriminate between damaged and undamaged fields then by random chance.

The available dataset on wild boar damage in grasslands was substantially smaller than for maize field (90 versus 185, Table 1), which resulted in model fitting issues when running the BRTs for grasslands as the model was not able to reliably discriminate between patches with and without boar damage. We therefore opted for grasslands for an alternative regression technique, namely 'BrGLMs' (bias reduction in binomial-response generalized linear models) using the brglm R-package (ver. 0.6.1, Kosmidis 2017). Here, relevant 'robust' predictor variables were selected using a model selection procedure based on Akaike's information criterion (AIC of the MuMIn R-package ver. 1.42.1, Barton 2018) in which AIC-values of all possible models (reflecting all possibilities of variable combinations) are first calculated. The relative importance of variables was then determined by summing the AIC-weights of all models in which a specific variable was included (Rouffaer et al. 2017). Robust variables are indicated by high AIC-weights (>0.5) and model-averaged estimates which are higher than their standard error (Burnham and Anderson 2002). Non-robust variables were removed from the model. 10-fold cross validation was used for the final set of robust variables in which the BrGLM is run 10 times, each time withholding randomly 10% of the data. Model estimates and AUC-values were then averaged over these 10 runs.

Projection of crop damage probability

We developed maps indicating damage probability for each field in Flanders, representing damage probability under the condition that wild boar would be present (as wild boar presence itself is not modeled here) and the crop in question would be cultivated at the specific field. Subsequently, we ran three model scenarios for both maize fields and grassland. For the first run, projections are only based on the landscape model, thus not incorporating field-specific variables, showing the spatial distribution of damage risk in Flanders due to landscape-level characteristics only. To simulate a 'worst case' scenario, the combined model including both landscape and field-specific variables was run whereby the field-specific variables, as this information is not available for all fields in Flanders, were set such that they result in the highest damage

risk (high risk scenario). A 'best case' scenario was then made with all field-specific variables in the combined model set such that they result in the lowest damage risk possible (low risk scenario). These high and low risk scenarios reflect the influence of field-specific variables on the damage probability extent and thereby the possible impact of changes in field-specific agricultural practices that farmers can implement or can allow farmers to consider crop planning changes.

Extrapolation outside the training range of the dataset of a SDM can return less reliable results (Fitzpatrick and Hargrove 2009). To quantify the degree of extrapolation in our projections, the extent of environmental differences between model training and projection data is calculated using multivariate environmental similarity surface (MESS) maps using the ecospat R-package (ver. 3.0, Broennimann et al. 2018). MESS-analysis measure the similarity between the dataset used to train the model and the newly projected areas. Positive MESS-values reflect that the full range of the new variable values are included in the original dataset, while negative MESS-values reflect variable conditions which are not included in the training data, thereby identifying areas where the model is extrapolating.

Results

Maize fields

Due to multicollinearity, the variables percentage of agricultural cover, percentage of urban cover and mean habitat patch size were removed from the dataset. Model selection of the landscape model resulted in the further removal of distance to nearest urbanized area, distance to nearest forest patch, distance to nearest road, road density and habitat patch density. The final landscape model for maize therefore consequently includes the percentage of maize, grassland, forest, urban area, hunting area and of scrub and other low natural cover within each buffer and the percentage of forested edge of the field (Table 4). For the field-specific maize model, model selection resulted in the removal of organic fertilization resulting in a final model including the precocity-value and inorganic fertilization.

Crop damage probability was best explained by the landscape model (AUC-value of 0.97) with the percentage of maize, grassland, forest and urban area within buffers being the most predictive variables (Table 4). The relationship between the variables and damage probability are visualized in Supplementary material Appendix 1.

The field-specific model showed the least explaining power (AUC of 0.73) with the precocity-value being the most predictive value. The combined model has a similar accuracy as the landscape model (AUC of 0.96) (Table 4). However field-specific variables in the combined model only contributed a small part (6.44%) to its predictive power.

Grasslands

Because of multicollinearity, the variables percentage of agricultural land, urbanized area and mean habitat patch size in buffers were deleted from the dataset. The final landscape grassland model includes distance to nearest forest patch and

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Table 4. Final landscape model, field-specific model and combined model with remaining variables for maize fields to explain crop damage probability by wild boar in Flanders. Variable importance (%) and model parameters (mean total deviance, training data correlation and AUC-value (area under the curve value)) are shown.

	Landscape model	Field-specific model	Combined model
Variable importance			
Percentage maize	16.32	/	15.29
Percentage grassland	16.89	/	17.23
Percentage forest	18.20	/	14.26
Percentage urban area	16.50	/	15.29
Percentage hunting area	11.57	/	10.94
Percentage forested edge	10.62	/	8.90
Percentage scrub and other low natural cover	10.90	/	11.66
Precocity-value	/	81.66	4.19
Inorganic fertilization	/	18.34	2.25
Model parameters			
Mean total deviance	1.34	1.37	1.37
Training data correlation	0.81	0.40	0.83
AUC-value	0.97	0.73	0.96
Model settings			
Learning rate	0.0005	0.005	0.005
Bag fraction	0.67	0.50	0.75
Tree complexity	3	1	2
Number of trees	9750	2650	1450

distance to nearest road as the only robust variables (Table 5). The final field model included organic fertilization, inorganic fertilization and grassland age.

The combined model shows the highest-AUC value (AUC of 0.91), thus the combination of field-specific and landscape variables explains damage probability of grasslands the best. The relationship between the variables and damage probability are visualized in Supplementary material Appendix 2.

Model projections to Flanders

Damage probability based on the landscape model of maize fields showed a heterogeneous distribution of damage probability in Flanders with a generally lower damage probability in the west compared to the east (Fig. 2a). Around urbanized areas, there is generally a higher damage probability although model extrapolation occurs in these region (MESS maps, Supplementary material Appendix 3). As expected due to the limited contribution of field specific variables to the total model, the high- and low risk scenarios show only a limited change in damage probability distribution and extent compared to the landscape model (Fig. 2b).

Damage probability based on the landscape model for grasslands shows an overall higher damage probability in Flanders compared to maize fields and less geographic variations (Fig. 3a). The high- and low risk scenarios show a large change in damage probability distribution and extent (Fig. 3b) compared to the landscape model reflecting the importance of field-specific characteristics. In general, for estimating grassland damage probability, model extrapolation did occur more compared to maize (MESS maps, Supplementary material Appendix 3).

Discussion

With an increasing number of human–wildlife impacts (HWI) due to damage to agricultural land in Flanders, there was an urgent need to better understand factors attracting wild boar to specific fields. Our research showed that landscape characteristics were found to have a more profound effect compared to field-specific characteristics when predicting damage probability for maize fields. For grasslands a combination of field-specific characteristics and landscape characteristics determine the damage probability.

As forest gives shelter to wild boar (Lombardini et al. 2016), the correlation between forest and damage probability in maize fields and from shorter distance to forest for grasslands was not surprising, and confirms results of previous studies (Ficetola et al. 2014 in Italy; Saito et al. 2011 in Japan and Daim 2015 in Germany). Damage risk increases when scrub and other low natural cover increases around a field. We consider scrub and other low natural cover, thus not only forests as such, a vegetation type which can provide sufficient shelter opportunities creating suitable wild boar habitat thus explaining the correlation with damage risk. An increasing percentage of grasslands in the direct surroundings of maize fields results in less shelter, which can explain the negative correlation between damage probability for maize fields and the presences of grasslands. Although maize also provides (seasonal) cover to wild boar (Schley et al. 2008), the negative correlation between damage probability and more maize cover can be explained by the balance between supply and demand of maize as a food source in the direct surroundings: the more maize is cultivated in the environment, the lower the damage probability of an individual field due to sufficient availability of maize as a food source.

Flanders has an extremely anthropogenic and fragmented landscape and is one of the most densely populated areas of Europe, Consequently our results do present interesting information on damage risk and damage patterns in highly anthropogenic landscapes. The specific variables we used to study the impact of fragmentation on wild boar damage probability (habitat patch density, mean habitat patch size and road density) were not significant questioning the importance of fragmentation in relation to damage probability. However, the percentage forested edge of a field, a parameter which is influenced by fragmentation (Davidson

Table 5. Final landscape model, field-specific model and combined model with remaining variables for grasslands to explain crop damage probability by wild boar in Flanders. Model parameters (average variable estimates, p-values and AUC-value (area under the curve values) over ten runes as well as the number of runes which were significant for each variable) are shown.

	Landscape model		Field-specific model		Combined model	
	Estimate	p-values	Estimate	p-values	Estimate	p-values
Intercept	1.0±0.17	0.00076±0.00087 10/10	2.31±0.32	0.037±0.015 8/10	2.50±0.29	0.041±0.023 8/10
Distance to nearest forest	−1.022±0.13	0.0065±0.0028 10/10		/	−0.30±0.20	0.52±0.20 0/10
Distance to nearest road	1.050±0.23	0.017±0.015 10/10		/	1.57±0.036	0.0053±0.0051 10/10
Age grassland		/	−0.52±0.18	0.18±0.078 1/10	−0.48±0.16	0.24±0.16 0/10
Use of organic fertilization			−1.89±0.14	0.019±0.0060 10/10	−2.25±0.25	0.021±0.021 9/10
No maize as previous crop			−3.02±0.52	0.050±0.0046 6/10	−5.73±0.63	0.0054±0.0027 10/10
Use of inorganic fertilization			2.06±0.20	0.010±0.0048 10/10	2.80±0.21	0.0044±0.0015 10/10
No maize as previous crop:Age			0.96±0.20	0.033±0.023 9/10	1.40±0.19	0.0087±0.0077 10/10
Model parameters						
AUC	0.74±0.016		0.83±0.015		0.91±0.013	

1998), had an effect on maize damage probability. We therefore suggest that further research into the relation between landscape fragmentation and wild boar damage probability is required. For such a study, variables related to the intertwinement of different forms of land use and fragmentation measures for both natural and agricultural biotopes should be used.

We only found an effect of the percentage land that was hunted once 90% or more of the area around a field is indeed included in hunting grounds. In these cases damage probability starts to decrease in maize fields. Although hunting has been found to be an effective method in reducing crop damage in an area (Geisser and Reyer 2004), it has been shown that the effect of hunting on spatial activity varies between hunting methods ranging from smaller home ranges to increased flee distances (Keuling et al. 2008). Moreover, battues effectively decreased crop damage while increased crop damage was caused by unregularly population control (Giménez-Anaya et al. 2016). In addition hunting pressure in an area can vary depending on the number of hunting days, intervals between hunting days and number of participating hunters and dogs. We therefore suggest to further investigate the mechanisms between hunting pressure, hunting methods and damage patterns as wells as wild boar movement before implementing or adjusting hunting strategies to decrease crop damage risk.

Field-specific factors play only a minor role in comparison to landscape factors for maize fields. This is in contrast to grasslands were fertilization, age of the grasslands and the crop of the previous year play an important role according to our grassland model. While the use of organic fertilization was found to have an inhibiting effect on damage probability for grasslands, using inorganic fertilization increases damage probability. Macro invertebrates like earthworms and grubs are part of the diet of wild boar (Barrios-Garcia and Ballari 2012) and macro invertebrate communities are affected by fertilization (Potter et al. 1985, Laznik and Trdan 2014). We thus assume that the effect of fertilization on crop damage probability could be explained through the effect of fertilization on this dietary source from wild boar: Laznik and Trdan (2014) found an increasing weight of earthworms in the soil with increasing K_2O-values and an increasing number of grubs with increasing P_2O_5 content, both being frequent components of inorganic fertilization. We thus expect this explains increasing rates of grassland rooting as wild boar root up macro invertebrates from the soil. Positive effects of the use of organic fertilizers on earthworm abundance have previously been demonstrated (Whalen et al. 1998, Daim 2015). Although this can logically also result in more rooting damage in fields using organic fertilizer, which we did not find in our study. However, as earthworm populations are also influenced by other factors such as soil temperature, chemical properties and moisture (Kanianska et al. 2016), a more extensive research towards dynamics of earthworm populations affecting rooting patterns of wild boar was outside the scope of this study. Furthermore, grassland damage probability increased with increasing grassland age. Only for new grasslands (0–1 year), damage probability did increase if maize was previously cultivated. As intense management of grasslands leads to decreased soil macro invertebrate biodiversity (Bardgett and Cook 1998), older grasslands in which
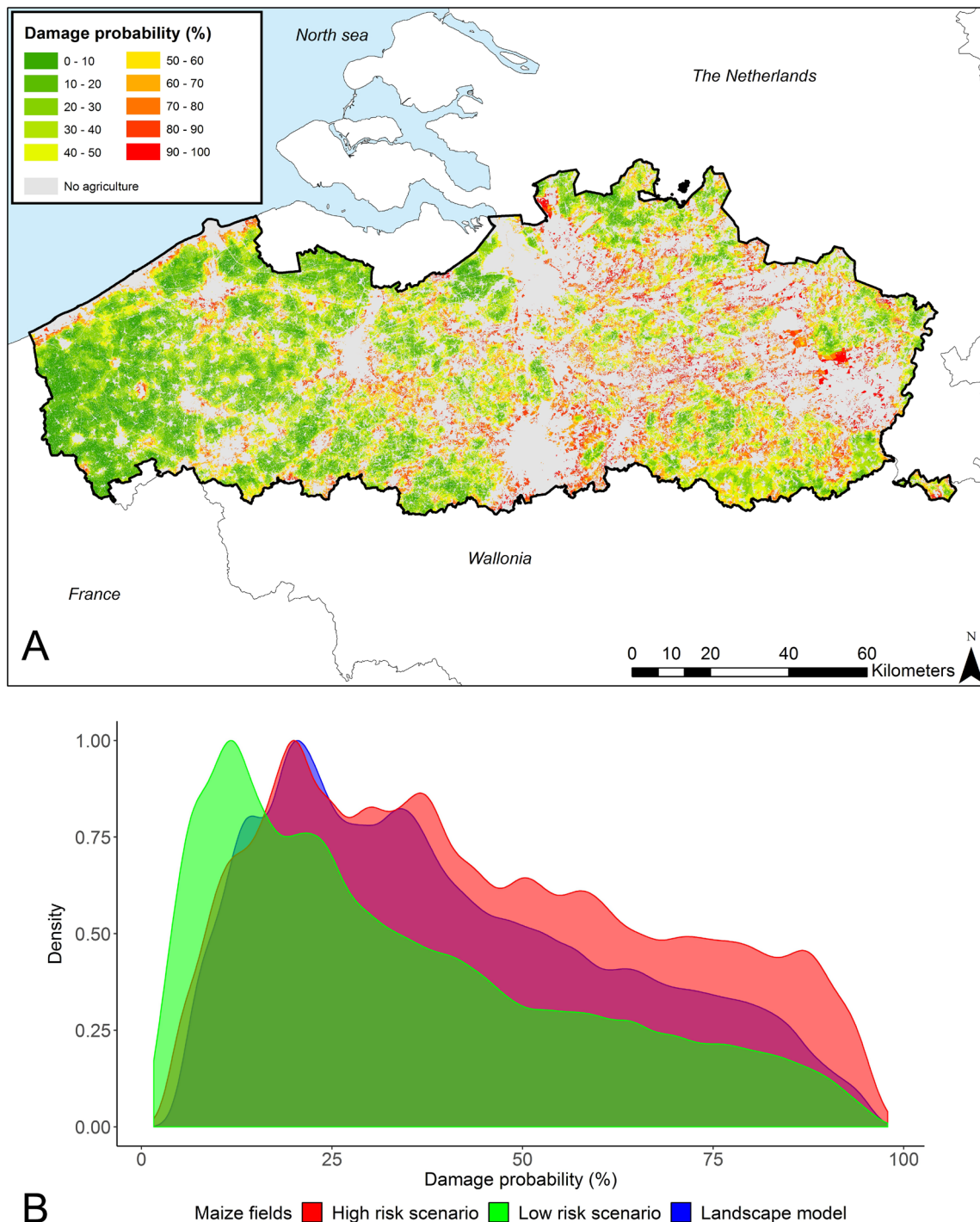
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Figure 2. (a) Projection on crop damage probability by wild boar for Flanders based on the landscape model for maize fields if on all fields maize was cultivated and wild boar are present and (b) the density distribution of damage probability in Flanders of a high risk and low risk scenario of the combined model compared with the distribution based on the landscape model.

soil biota can develop with time results in a more diverse dietary source which has been found to be preferred by wild boar (Bueno et al. 2009).

Making projections based on the maize- and grassland landscape models results in projection maps of the potential risk and geographical distribution of crop damage in Flanders. These projection maps represent the situation under the presumption that wild boar would recolonize the whole region. In maize fields, a generally higher damage probabil-

ity for an individual field was found in the east compared to the west. However, we want to point out that, due to a larger percentage of the area used for agriculture in the west of the region, the overall economic impact of wild boar crop damage could still be higher in the west compared to the east. Furthermore, although agricultural fields around large urban areas seem to have a high damage probability, it should be noted that it is also in these regions that our distribution models are most strongly extrapolating beyond the range of
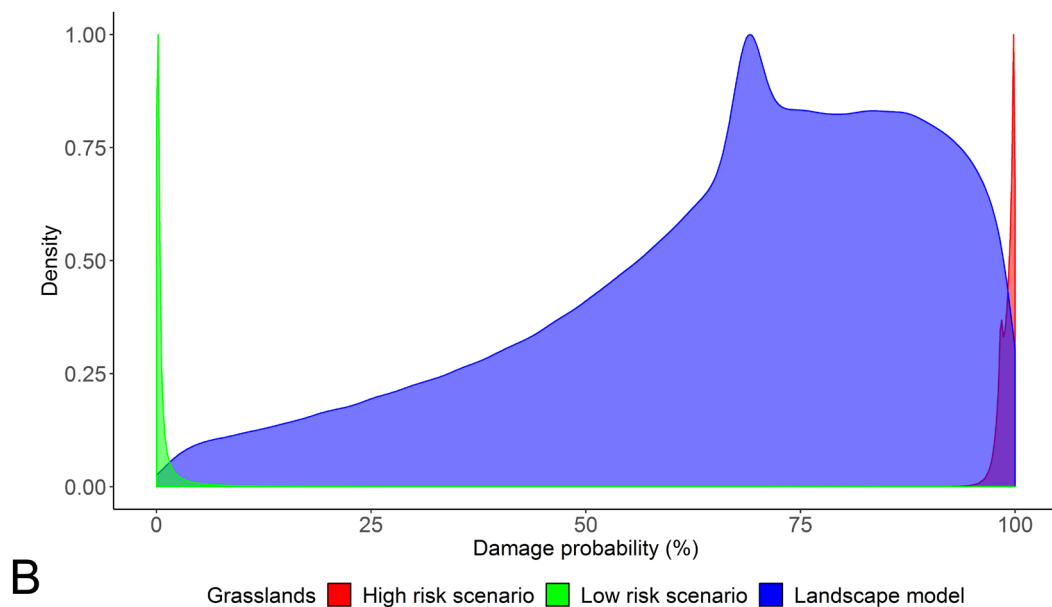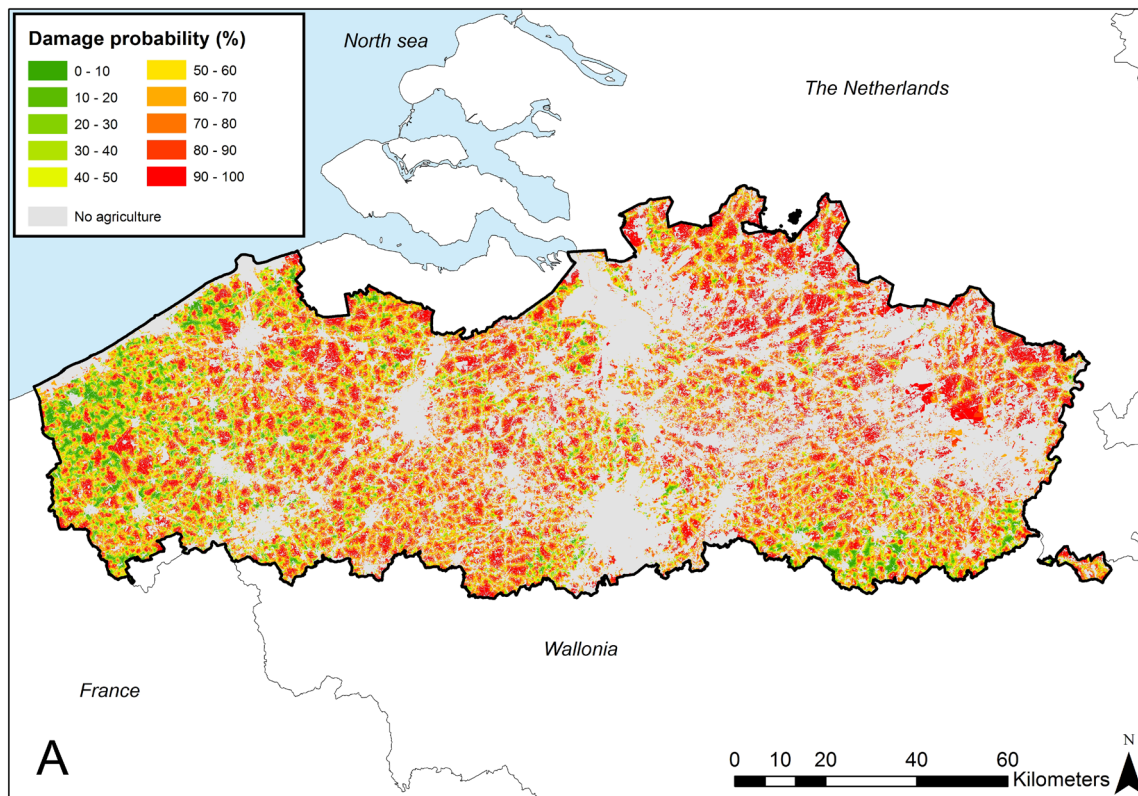
Figure 3. (a) Projection on crop damage probability by wild boar for Flanders based on the landscape model for grasslands if on all fields grasslands were cultivated and (b) the density distribution of damage probability in Flanders of a high risk and low risk scenario of the combined model compared with the distribution based on the landscape model.

model training conditions. As the training set of the model originates from the current distribution area of wild boar, which is not as urbanized as the most extremely urbanized regions in Flanders, the projections around highly urbanized areas are less reliable requiring further model training with wild boar expanding towards extremely urbanized regions. The high- and low risk scenarios finally reflect the influence of field-specific variables on damage probability and thereby also to which extent the adjustment of these variables could lead to mitigating damage risk. The difference between high- and low risk scenarios was found to be low for maize field projections due to the limited influence of field-specific factors of crop damage probability. However, we found large differences in the overall extent of damage risk under the different scenarios for grasslands. The high risk scenario showed an overall extreme high damage risk for the whole region of

Flanders while the low risk scenario showed an overall low damage risk in grasslands. This reflects the large influence of field-specific variables compared to the influence of landscape variables, thus highlighting the potential high impact of agricultural management decisions on grassland damage by wild boar. Adjusting fertilizing for grassland might however result in lower yields and consequently lower revenues (Schläpfer et al. 2002, Di Paolo and Rinaldi 2008) and grasslands provide important ecosystems services (Wrage et al. 2011) thus the impact of certain agricultural management decisions should carefully be considered. For maize fields, adjusting agricultural practices to affect field-specific damage risk will be less effective although here, the implementation of preventive measures (i.e. electric fences) can now be targeted more efficient as well as targeted crop planning can allow to grow maize on low damage risk fields and grow other crops in high damage risk fields (if maize would be planted).

Management implications

Damage management is an important part of wild boar management. Understanding the impact of certain agricultural practices like crop selection, fertilization, crop variety etc. on damage risk can help farmers to decide on crop planning strategies or help to target effectively the implementation of preventive measures. This will reduce HWI's by wild boar and consequently increase stakeholder acceptance of wildlife (Messmer 2009, Young et al. 2010).

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Supplementary material (available online as Appendix wlb-00634 at <www.wildlifebiology.org/appendix/wlb-00634>). Appendix 1–3.