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Forest structure, roads and soil moisture provide realistic predictions of fire spread in modern Swedish landscape

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ABSTRACT

Recent increases in fire activity in Sweden call for the quantification of forest fire susceptibility, in order to develop management strategies to mitigate fire risk. Using the data from 100 large Swedish forest fires (>10 ha), mapped from sentinel-2 images from 2016 to 2022, we explored the predictive power of vegetation properties in estimating relative likelihood of fires within a landscape using logistic regression. To model spatially explicit fire susceptibility within a given landscape, we used the outcome of logistic regression as an input into a cellular automata model (CA model), which simulates fire spread in a 2D grid.

The CA was model calibrated on three fires that occurred between 2016 and 2022, then verified on six 2023 fires and featured a mean sensitivity of 0.74 and specificity of 0.79. The logistic regression model had an accuracy of 54 %, showing increased fire susceptibility from high Scots pine volume (p-value = 0.02), and decreased fire susceptibility from high volumes of deciduous trees and wet soil. Realistic outcomes of the CA model and reliance of our approach on publicly available data with nation-wide coverage of vegetation cover in Sweden allows for the development of an automated protocol of fire susceptibility assessment at the operational level and its integration in existing decision support systems. This would allow forest owners to obtain estimates of forest fire susceptibility for different forest management strategies.

1. Introduction

Forest fires have been a major disturbance shaping boreal landscapes over the Holocene (Carcaillet et al., 2001; Kuosmanen et al., 2016). Under natural conditions, fires drive natural forest succession, shape forest structure and biodiversity, and mediate biogeochemical cycles (Hollingsworth et al. 2013). In Sweden in the 1800s effective fire suppression, and possibly a less fire prone climate, reduced fire's importance as a factor controlling the structure of boreal vegetation (Drobyshev et al., 2012). However, the future climate will likely be more prone to forest fires (Krikken et al., 2021), which could challenge the capacity of modern society to efficiently mitigate fire risks.

In the boreal zone, regional forest fire activity is closely related to natural interactions between climate and fuel conditions (Flannigan et al., 2001; Flannigan and Harrington, 1988). The development of the Canadian Forest Fire Danger Rating System (CFFDRS), including the Forest Fire Weather Indices (FWI) and Forest Fire Behaviour Prediction System (FBP), has been of critical importance for quantifying and analysing the temporal dynamics of weather and fuel drying as controls of fire hazard (Turner and Lawson, 1978; Wotton, 2009).

Fire spread and behaviour models, such as the Canadian Forest Fire Behavior Prediction System were built using data from empirical field experiments and lab-based physical fuel models (McAlpine et al., 1990; Wotton, 2009). These hybrid physical or semi-empirical models are developed for a specific region and require substantial data collection to develop region-specific fuel models (McAlpine et al., 1990; Wotton, 2009). This extensive data collection for the parameterization of a Swedish fuel model has not yet been undertaken. Specifically, in Sweden there are no spatially explicit models of fire activity, precluding the use of available data on forest structure to assess fire risk in operational settings. Low forest fire activity in Sweden during 1900s and most of the 2000s (Drobyshev et al. 2012) was a likely reason for such a lack of interest in fire modelling.

Empirical (statistical) models relating properties of vegetation cover

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with the probability and properties of fire disturbance offer an alternative, and generally less data intensive pathway, to model forest fire susceptibility at landscape scale (Adab, 2017; Pourghasemi, 2020; Preisler et al., 2004). Forest fire susceptibility is defined as the probability that an area of forest will burn based on the forest characteristics of the location, excluding temporal aspects (Leuenberger et al., 2018). Such models can be calibrated using openly available remote sensing data (Ciesielski et al., 2022; Shang et al., 2020). Specifically, fire perimeters and forest characteristics (stand structure and composition), can be deduced from satellite imagery and used to model fire susceptibility.

The outputs from empirical models can be used to develop transition rules for cellular automata (CA) models. CA models simulate fire spread across a two-dimensional grid, adding a spatially explicit component in fire modelling. Application of CA models in fire susceptibility prediction has evolved from a purely theoretical concept to being able to calibrate transition rules based on the fine-scale vegetation structure and topography (Karafyllidis and Thanailakis, 1997; Sun et al., 2024). These transition rules define the paths of least resistance through which a fire is likely to move through the landscape, and can be defined either based on several mechanistic assumptions (Trucchia et al., 2020) or derived from fire susceptibility functions (Zheng et al., 2017; Jellouli and Bernoussi, 2022; Sun et al., 2024).

From the second half of the 20th century and into the early 21st century, the weather conditions in Sweden have exhibited increased temperatures, and likelihood of heatwaves (Wilcke et al., 2020), which promote fire prone weather conditions. While the long-term average annual area burned in Sweden is around 2900 ha (Sjöström and Granström, 2022), forest fires in 2014 burned 12 500 ha and in 2018 burned 22 000 ha, causing considerable costs to Swedish society (Eriksson et al., 2018). This observed increase in the number of large fires in Sweden may indicate we have reached the capacity limit of modern fire suppression. Future climate projections predict increased fire season length, wildfire frequency and severity in Sweden (Krikken et al., 2021). There is an increasing need for new management strategies, which would integrate emerging fire risk into a wide range of Swedish forest-related industries.

The current study evaluated the potential use of available Swedish forest structure and soil moisture maps to assess forest fire susceptibility. We hypothesized that: (H1) forest structure (tree species) and soil moisture are informative predictors of forest fire susceptibility in Sweden. Alternatively, forest fire susceptibility may be more strongly influenced by other environmental factors, such as topography and climate. We developed statistical models operating on a subset of larger (> 10 ha) modern (2016–2022) forest fires to identify forest properties that increase burn likelihood in the presence of ignition. We then used the best statistical model to drive a cellular automata model (CA model) to provide a spatially explicit analysis of fire behaviour. The CA model integrated the spatial distribution of predicted fire susceptibility and firebreaks, including roads, to model fire spread. We evaluated CA model performance on selected fire-affected landscapes using fire perimeter maps of true area burned. The study time-period was defined by the availability of sentinel-2 remote sensing products for the accurate delineation of fires.

2. Methods and data

2.1. Study area

Sweden is located in Northern Europe, on the Scandinavian Peninsula. The North Atlantic Current and North Atlantic westerlies define the southern region's milder oceanic climate, due to the warm North Atlantic Current (Roberge et al., 2020), whereas a colder continental climate occurs in the north (Roberge et al., 2020; Wastenson et al., 1995). The North and South have similar summer temperatures; however, winter temperatures vary widely, where mean January temperatures are -14 °C in the north and just 0 °C in the south. Precipitation has a pronounced east-west gradient, with higher rainfall occurring in the west and ranges from 500–2000 mm per year (Wastenson et al., 1995).

The natural vegetation ranges from nemoral (temperate broadleaved forest) in the South to alpine in the North and encompasses six biogeographical zones (Wastenson et al., 1995). Sweden is mostly forested (~69 % of the surface area or 27.9 million ha), the majority of which is production forest (23.5 million ha, Roberge et al., 2020). The predominant production forest species are Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*) making up 39.3 % and 39.7.7 % of growing stock volume respectively (Nilsson et al., 2021).

2.2. Data preparation

We digitized fire perimeters using available cloudless post-fire optical images from Sentinel-2 satellites (10 m resolution). False-colour composites (band combination Near Infrared – Red – Green) were visually examined on the Sentinel Hub EO Browser at hotspots of thermal anomalies from the FIRMS active fire product. We aggregated centroids of FIRMS pixels, if they shared the same date, in Google Earth Engine and extracted only the centroid points of these aggregations ('hotspots'). If the burned area was larger than 10 ha, then the image chip was downloaded, and the fire perimeter was manually digitized in the ArcGIS environment. We excluded unburned internal patches of forest from fire perimeters. We did not include fires exceeding 1000 ha that occurred during 2018 in the analyses. We argued that these large fires occurred during conditions of extreme climatological fire hazard, under which fuels burn indiscriminately, homogenizing the susceptibility of different fuel types to fire. We digitized 162 fire perimeters of 100 distinct wildfires from 2016 to 2022 (Fig. 1a), which were used in the statistical susceptibility analysis. Additionally, we digitized all six of the large (>10 ha) forest fires that occurred in 2023 which were used to verify the CA model, so as not to use the same fires to train and verify the final model.

We used the SLU Soil Moisture Map (SLU, 2020) with three discrete soil moisture classes: 1 – dry, 2 – mesic, 3 – wet and open water bodies. The original resolution of this map was 2 m, hence, it was resampled to 25 m using nearest neighbour interpolation to match the resolution of other raster layers. Land cover data was extracted from Svenska CORINE marktäckedata, SCMD, the Swedish implementation of CORINE Landsat classifications (Ahlcrona, 2003). Finally we used raster maps at 25 m spatial resolution from SLU Forest maps 2010 (Reese et al., 2002, 2003), which are the latest published data with forest volume covering all the whole country. We extracted the total forest volume (m^3 ha^{-1}), volume of pine (*Pinus* spp.), spruce (*Picea abies)* and broadleaves. Broadleaved volume was the cumulative volume of birch (*Betula* spp), oak (*Quercus* spp.*),* European beech (*Fagus sylvatica* L.) and the volume of "other broadleaves".

The SLU Forest map data on standing volume (2010) preceded the actual fires by between 6 and 12 years, necessitating map corrections to account for forests that were harvested after the maps were made. To address this, we obtained all polygons of clear-cuts from the Swedish Forest Agency between 2000 and 2021 (Skogsstyrelsen, 2021), and if tree harvest was conducted between 2010 (year at which raster maps were produced) and the year of the respective wildfire, we converted these pixels to non-forest area and excluded them from the further analysis (Fig. 1b). We also excluded all pixels intersected by water bodies, rivers (Swedish National Land Survey, 2021), railroads, or roads (Trafikverket, 2022) in the same way.

We sampled forest structure and soil moisture at random points in burned areas and within 30 m wide buffers around the fire perimeter. By sampling unburned points from such a narrow buffer, we assumed that the probability of burning in this area was controlled by fuel properties and was not limited by the probability of ignition.

The sampled points were at least 200 m away from each other to reduce spatial autocorrelation. In total, we sampled 1155 points: 917 within fire perimeters and 238 within unburned buffers.

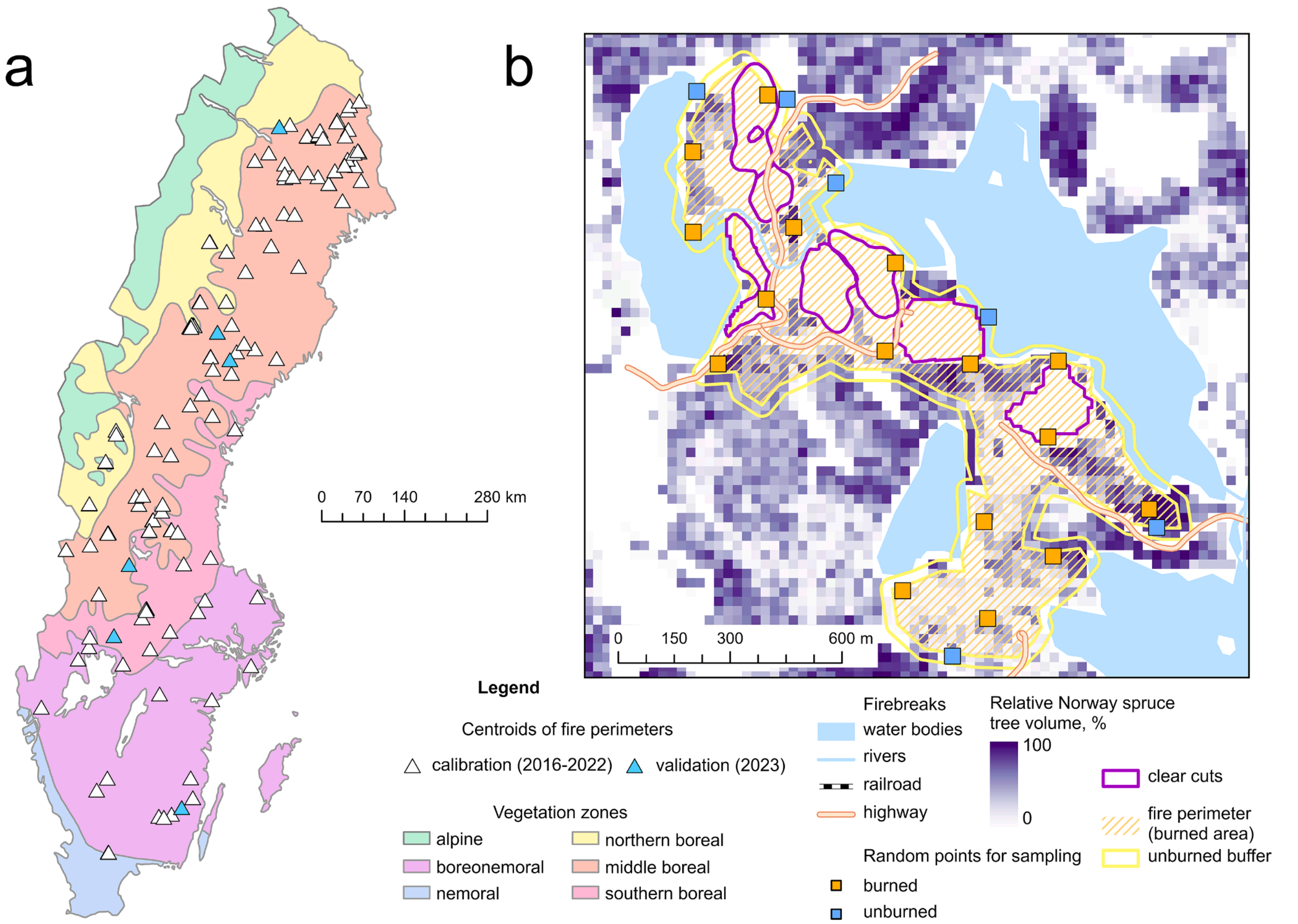

Fig. 1. Location of fire perimeters used in the study within the vegetation zones of Sweden (a); an example of a digitized fire perimeter and its unburned buffer zone (b).

We extracted forest properties and soil moisture data for each sampled point. We selected 238 of the 917 points for the 'burned' subset to match the size of the 'unburned' subset.

2.3. Fire susceptibility statistical model

We modelled fire susceptibility as a function of forest fuel structure approximated by forest type, standing volume, and soil moisture conditions. We wanted to investigate all available map data sources and ensure that our model provided the best approximation of forest fire susceptibility. To test the utility of increasing levels of detail in forest structural data, we carried out the modelling in three stages. In the first stage, the model tested soil moisture conditions on forested land, with no information on the forest structure itself. The second stage model tested a combination of soil moisture conditions and land cover data that classified vegetation into four forest types: coniferous, broadleaved, mixed species stands or temporarily non-forested (predominantly clear-cuts). In the third model, forest cover data was replaced with the best available spatial resolution open-source information on forest structure, providing standing volume estimates for pine, spruce, or broadleaved species.

We fit the models on a subset of 79 % of the data, taken from both the fire perimeters and buffers, and used the remaining 21 % to validate the models.

We developed a logistic regression model

$$\ln\left[\frac{P_x}{1-P_x}\right] = \beta_0 + \beta_1\ X_1 + \beta_2\ X_2 + \beta_3\ X_3 \ldots\ldots$$

where P_x is the probability of success (response variable is 1), β_0 is the intercept, β_1 X_1 is the slope of the first explanatory variable, β_2 X_2 is the slope of the second explanatory variable.

This parametric binary classification approach allowed us to estimate a statistical significance of the model predictors. We tested the model fit using the R package *DHARMa* (Hartig and Lohse, 2022) by using Kolmogorov-Smirnov test to compare distributions and Moran's I test to evaluate residual spatial autocorrelation. We relied on R package *mctest* (Imdad et al., 2019; Imdad and Aslam, 2018; Imdadullah et al., 2016) to identify the multi-collinearity between predictors, using variance inflation factor with a maximum of 5. The model generated a fire susceptibility map, which showed the likelihood of each pixel to be 'burned' as a value ranging from 0 to 1. Depending on the model (Table 1), the predictions were based on soil moisture classes (model # 1), soil moisture classes and forest types (model # 2), and soil moisture classes and tree species volume (model # 3).

2.4. Cellular automata model

We used a cellular automata model (later referred to as CA model), to model fire behaviour in a forested landscape using maps of roads, firebreaks and predicted fire susceptibility maps from our statistical model (see above). The CA model generated the relative probability of burning of each cell in a landscape, should effective ignition take place.

The CA model simulated cell-by-cell fire propagation in forested landscape represented as a set of 25 × 25 m cells. For a single fire spread experiment, we randomly placed three ignitions within the landscape in

Table 1
Summary of candidate fire susceptibility models.

Variable	Estimate	Standard error	*p*-value
Model No 1 Soil moisture classes			
Intercept	0.05	0.13	0.70
Indicator of mesic soil moisture	-0.22	0.26	0.39
Indicator of wet soil moisture	-1.96	0.55	<0.01
Model No 2 Land cover types and soil moisture classes			
Intercept	-0.05	0.14	0.74
Broadleaf forest class	-0.57	0.72	0.43
Mixed forest class	0.29	0.51	0.57
Non-forest class	0.45	0.26	0.09
Indicator of mesic soil moisture	-0.24	0.26	0.36
Indicator of wet soil moisture	-2.01	0.55	<0.01
Model No 3 Species-specific volume predictors and soil moisture classes			
Intercept	-0.11	0.25	0.66
Pine volume	0.01	0.00	0.03
Broadleaf volume	-0.03	0.01	0.01
Spruce volume	0.00	0.00	0.29
Indicator of mesic soil moisture	-0.14	0.27	0.59
Indicator of wet soil moisture	-1.76	0.56	<0.01
Final model			
Intercept	-0.12	0.23	0.61
Pine volume	0.01	0.00	0.02
Broadleaf volume	-0.02	0.01	0.01
Indicator of wet soil moisture	-1.77	0.55	<0.01

question. To propagate fire beyond the cell where ignition took place ("ignition cell"), we sampled a value from a random uniform distribution constrained by 0 and 1 and compared it with the cell-specific probability of being burned (obtained through application of fire susceptibility model). If the random number fell below that probability, the CA model "burned" that cell. After going through a subset of cells bordering with the "ignition cell", the CA model revisited cells that bordered the burning cell and used the same uniform distribution approach to evaluate which cells should be burned (SI Fig. 4).

The CA model employed several "stoppage rules" that defined the moment when each fire experiment was considered complete. First, we allowed the model to attain at least 50 iterations to ensure that fires could attain a minimal spread (typically reaching the size of few hectares) before any stoppage rules were applied. The model stopped the experiment when the increase in the total burned area per iteration fell below 0.1 % of the total forest area in the studied landscape or until one-third-of the landscape burned. We assumed that under this condition, fire suppression efforts to control fire would effectively prevent fire from further spread. At maximum, a single fire experiment was allowed to reach 1000 iterations, and 500 fire experiments make up one run. One run is carried out on each landscape to simulate fire spread. (Figure 5 in SI).

Forest roads are an important modifier of fire suppression effectiveness in modern Sweden. Road density positively affects the number of ignitions and negatively affects the size of fires (Pinto et al., 2020). Since our statistical fire susceptibility model did not explicitly calibrate the relationship between road density and fire spread, we empirically estimated this using a "proximity coefficient" and a "road coefficient parameterized from a subset of 3 fires. The proximity coefficient defined the spatial extent of the effect, i.e. distance from the road at which a reduction in burn probability took place. The road coefficient defined the intensity of road effect, i.e. level of reduction in the burn probability for road-affected cells. In particular, we allowed these coefficients to vary from 0 to 1 (road coefficient) and from 1 to 7 (proximity coefficient). The road coefficient of 0 implied that cells crossed by the roads had zero probability of being burned, while the value of 1 implied no change in the burning probability, associated with the presence of the road. In the case of proximity coefficient, "1″ indicated a situation where reduction in burning probability was applied only to the cells crossed by the road; "7″ indicated that the effect extended up to seven cells away from the road (with linear distance from the road being 210 m). We tested for 20 unique values randomly sampled for respective ranges of each coefficient, resulting in 400 unique coefficient combinations. For each combination, we ran a simulation consisting of 500 runs (each – with up to 1000 single experiments) and calculated verification statistics (see below). By exploring the pattern of such statistics, we selected the optimized values of coefficients, which were later used to run the CA model (Figure 6 in SI). Specifically, the algorithm tracked the value of the skill statistics (see below) and selected combination of coefficients that tended to maximize its value within fire-affected landscape.

The outcome of the CA model was a matrix of cell-specific relative burn probabilities, i.e., estimates of forest fire susceptibility. To obtain these estimates, the model kept track of the number of times a cell was "burned" by the model, and divided it by the total number of experiments in a run (there are 500 fire experiments in one run). (Figure 5 in SI).

To evaluate performance of the CA model, we ran it on landscapes with fires that occurred in 2023. We hypothesized that the model would project higher probabilities of fire for true burned cells compared with the whole landscape (composed in reality of both burned and unburned cells). To test this assumption, we used Kolmogorov-Smirnov test and a measure of model skill based on the normalized difference in the probabilities of two groups of cells:

$$model.skill = \frac{P_{burned} - P_{all}}{P_{all}},$$

where P_{burned} and P_{all} were the mean probabilities of burning for true burned and all cells, respectively. A value of *model.skill* above zero would be indicative of skill which is a better than a random guess.

We validated the model on data from six fires that occurred in 2023. We calculated road network density (proportion of number of cells with roads to total number of cells), species-specific volume proportions to total volume stock, and proportion of cells with wet soil moisture (class = 3) to total number of cells in landscape. We extracted these metrics to understand how they could contribute to model skill for a specific validation site (Table 2).

We calculated false positive and false negative rates (FPR and FNR respectively) for each landscape for relative probability thresholds starting from the 0 to 100 percentile. For each fire landscape, we selected the optimal threshold as the percentile with lowest cumulative FPR and FNR, sensitivity and specificity values were calculated at these thresholds for each individual landscape (Table 3 in SI). The optimal

Table 2
Results of CA model runs on fire-affected landscapes used for validation, using the optimal threshold percentile of 0.73, and proportion of the landscape allocated to each variable.

Fire landscape Num.	Model Skill	KS Test *p*-value	Sensitivity	Specificity	Road density	Proportion of the landscape		
						Pine	Deciduous	Wet
1	0.98	0.00	0.93	0.83	8.46	58.80	9.55	0.88
2	0.51	0.00	0.71	0.78	7.64	48.23	16.12	1.10
3	0.06	0.00	0.13	0.73	5.62	79.13	3.57	0.80
4	1.29	0.00	0.82	0.78	5.52	61.87	16.54	9.11
5	0.55	0.00	0.97	0.82	0.00	34.19	18.45	8.52
6	0.86	0.00	0.87	0.78	3.35	56.81	14.19	9.42

threshold for our CA model was the mean of optimal threshold percentiles across all fire landscapes, and sensitivity and specificity were calculated for all fire landscapes using this threshold (Table 2).

3. Results

3.1. Fire susceptibility model

The logistic regression model candidates showed varying performance in predicting fire susceptibility. Upon validation, model #1, trained only with soil moisture indicators as predictors achieved 59 % overall accuracy, 36 % sensitivity (true positive rate) and 70 % specificity (true negative rate).

Model # 2, trained with forest cover type and soil moisture indicators performed worse, with 40 % overall accuracy, 72 % sensitivity, and 24 % specificity. Model #3, based on species-specific volume estimates and soil moisture indicators achieved 54 % overall accuracy, with 58 % sensitivity and 52 % specificity.

The ability of the models to distinguish between dry and mesic soil moisture class was poor (p-value = 0.59), therefore the dry and mesic moisture classes were pooled. Wet soil was a significant predictor in all three models. Additionally, pine volume and broadleaved volume were significant in model 3. Model 3 was selected as the final model and non-significant predictors (indicator of mesic soil moisture, and spruce volume) were removed.

Findings from our final model suggest (1) there is no deviation between observed and simulated data (Kolmogorov–Smirnov test p-value = 0.55), (2) predicted data was not spatially autocorrelated (Moran's I test p-value = 0.86) and (3) our predictor variables did not produce strong patterns of collinearity.

The final calibrated model tended to predict higher fire susceptibility for pine stands with high growing stock volume and in drier soil conditions. Whereas increased broadleaved volume stock resulted in lower fire susceptibility (Fig. 2).

3.2. Outcome of cellular automata model

Following parameterization, we selected 0.25 as the road coefficient value and 7 as the value of proximity coefficient. The CA model produced satisfactory results in five of six cases, the exception being landscape #3, which performed poorly in all performance indicators (Fig. 3 and Table 2). Kolmogorov-Smirnov p values for all landscapes were below 0.05, indicating the model projected higher probabilities of fire for the true burned cells than for that of the whole landscape.

With the exception of landscape #3, model skill ranged from 0.51 to 1.29. Sensitivity and specificity were also high and well-balanced indicating that the CA model neither over nor under predicted fire susceptibility. The majority of burned pixels had high predicted probability of burning (Fig. 3C where the distribution of fire probability of burned pixels are located to the right of the graphs for all landscapes).

Model skill was highest in landscape #4 (1.29), which had a high proportion of pine, deciduous trees and a high number of cells with wet soil. Landscape #1 had very high sensitivity at 0.93 and the highest specificity at 0.83, road density was high but did not confine the fire perimeter. Landscape #3 had low model skill of just 0.06 and sensitivity of 0.13 showing a high number of false negatives and the fire perimeter showed high conformity to the road. (Fig. 3B and C).

4. Discussion

4.1. Performance of fire susceptibility model

Forest structure and soil moisture provided realistic estimates of forest fire susceptibility in Swedish forested landscapes. Scots pine standing volume increased fire susceptibility, reflecting the availability of easily burnable fuels in pine stands. In Sweden, stands dominated by pine commonly occupy drier areas of the landscape (Päätalo, 1998) which further increases their susceptibility to wildfire. Alternatively, an increase in the volume of deciduous species lowered fire susceptibility, broadly supporting the view of deciduous vegetation as less flammable due to higher water content, as compared to coniferous fuels (Päätalo, 1998; Plathner et al., 2022). Stands with a dominant deciduous component grow in wetter conditions, i.e. habitats evidently functioning as firebreaks under moderate levels of climatological fire hazard. In line with this interpretation, soil dryness, which was included in the analyses as an independent factor, revealed a positive relationship with fire susceptibility.

Surprisingly the stand volume of Norway spruce neither significantly increased nor decreased forest fire susceptibility. It is likely that other landscape factors are more influential in controlling whether a spruce

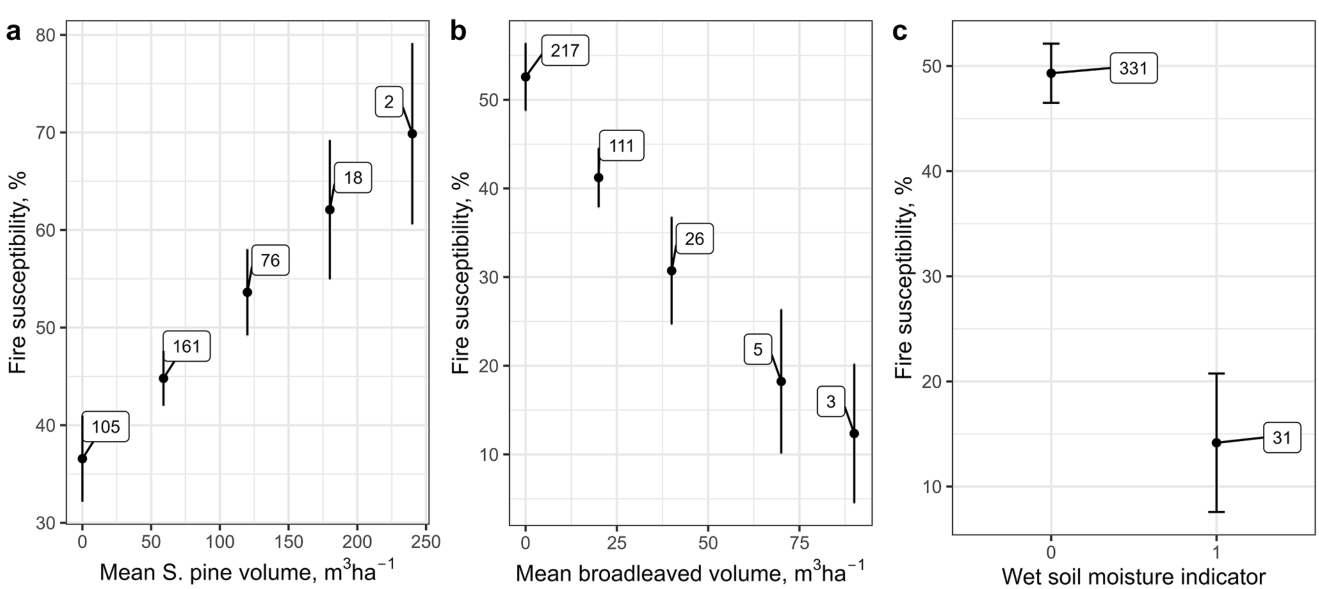

Fig. 2. Estimated linear effects of different predictors in the final fire susceptibility model: Scots pine volume (a); broadleaved volume (b); wet soil moisture indicator (c). Numbers in labels correspond to the number of points within quantile group (a-b) or specific soil moisture class (c).

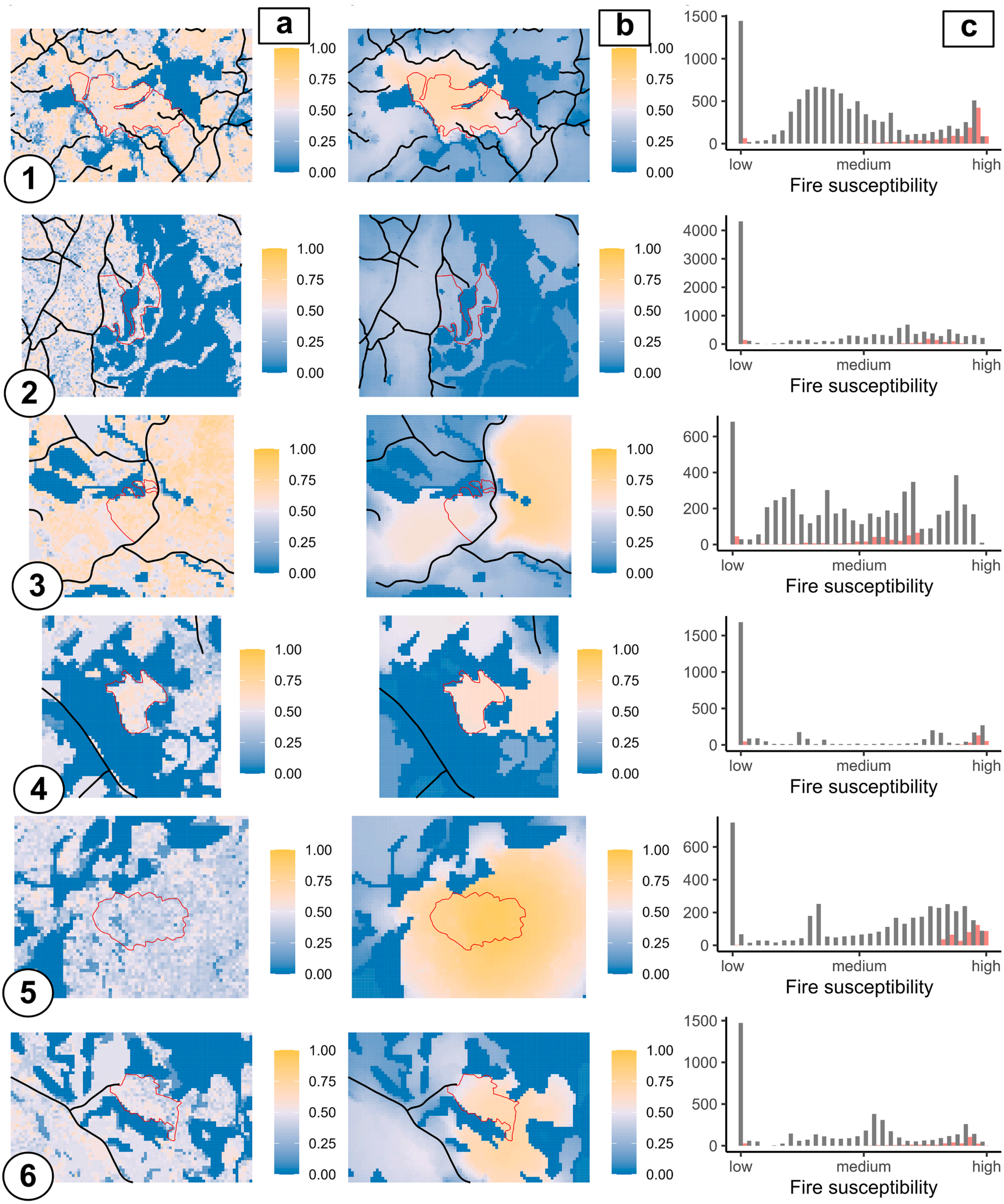

Fig. 3. Model predictions for validation sites: (a) fire susceptibility as assessed by empirical model; (b) fire susceptibility as assessed by CA model; (c) distribution of fire susceptibility for all (grey) and true burned pixels (red).

forest burns, for example, differences in likelihood of burning under different climatological conditions, stand age (Päätalo, 1998) or topography (Zackrisson, 1977).

4.2. Cellular automata model and its utility

Our CA model provided realistic burn probability predictions for five out of six landscapes, with model skill being well above zero. Model sensitivity and specificity values (Table 2) were high and balanced, indicating the model neither over- nor under-predicted probability of burning. We found that the CA model performed best in archetypal Swedish landscapes, i.e. those featuring forestry roads, heterogeneous forest structure, dominant pine and moderate abundance of deciduous trees. In contrast to other fire behaviour simulators, which rely on mechanistic fuel models and are intensive in terms of data, resource and computational effort (Trucchia et al., 2020), our CA model relied on a minimal set of variables and publicly available data. These settings allow for potentially universal applicability of our approach across Swedish production forests and possibly other Nordic countries with such data available.

CA model skill showed variability as a function of road density in a landscape. In areas with no roads, such as landscape # 5, the CA model skill declined. On the one hand, this result indirectly supported our parameterization of the road effects. Indeed, the CA model treated roads as "reducers" of fire susceptibility and the improved performance seen in landscapes with high road density suggested realism in defining road and proximity coefficients (see *Methods* section). On the other hand, lower skill in "roadless" landscapes pointed to limited skill of the model in predicting fire spread across vegetation cover not fragmented by roads. This is not surprising as the CA model did not use topography nor wind data as inputs, in contrast to majority of existing studies modelling fire behaviour (Pham et al., 2020; Pourghasemi et al., 2020; Sachdeva et al., 2018; Sadat et al., 2016).

Despite the fact that the fire susceptibility was generally better predicted in landscapes with higher road densities, we frequently observed false negatives in parts of the forests studied where fire perimeters closely conformed to roads. In these cases, an area of low probability was predicted nearer the road and yet all pixels up to and conforming to the road did burn. Landscape # 3 illustrated this pattern well, with the road defining the entire eastern fire perimeter and the model sensitivity being low (Fig. 3). This pattern might indicate roads were used as actual fire breaks with fire suppression effort during actual fire, which did not extend away from the road into the burning stands. The result might also suggest differences in the road impact on fire susceptibility, which are dependent on local geographical context or type of roads.

4.3. Methodological implications and study limitations

The complexity of fire behaviour parameterization often prevents its efficient application in operational forest management. Integration of functional relationships between fire, fuels, topography and local climate requires massive data acquisition campaigns (Beverly and McLoughlin, 2019), which are prohibitively costly for the majority of forest managers. Our study demonstrates that a limited number of variables from open-source datasets can provide robust inputs into spatially explicit models generating skilful predictions of fire susceptibility.

The incentive to develop a new CA model was based on the observation that existing CA models need data inputs which are not currently available for the entirety of the Swedish forests. Our model, in contrast, relied only on publicly available datasets that cover all forests in Sweden. This ensures applicability of the model in operational planning carried out by forest companies and private forest owners, which do not commonly engage in acquisition of data on forest fuels.

Climate datasets available for the region are much coarser spatial resolution than that used in our modelling approach, with no ability to distinguish between variation in climatological conditions between 25 × 25 m^2 raster cells or within our burned and non-burned sites. The exclusion of climate data as predictor variables in our models is lamentable, but unfortunately impossible to obtain at this spatial scale for past fires.

Poor representation of periods with extreme climatological fire hazard and limited number of fires used for model calibration were shortcomings of our analyses, which we plan to overcome during subsequent model development. Both are instrumental for realistic modelling of fire spread. Periods of extreme fire hazard homogenize forest fuels, effectively minimizing differences in their ability to carry fire among different forest fuel types and making the whole landscape prone to fast fire spread. Such conditions warrant an independent parameterization effort, relying exclusively on fires that spread during such conditions. In turn, the low number of fires analysed likely limited our ability to capture a wider variability in vegetation cover as predictor of fire spread. This low number of fires was a product of generally low levels of fire activity in modern Sweden and our interest to minimize the effect of active fire suppression through selection of large fires (see Methods section). Future study may overcome this shortcoming by aggregating data on older fires and, possibly, changing the fire size threshold used in this study. Finally, quality of vegetation cover data might have an effect on statistical skill of developed models. The SLU Forest Maps 2010 are an approximation of parameter values from 2010, as such forest parameter values were between 6 and 12 years out of date for each fire event. SLU Forest maps have lower accuracy estimates of deciduous tree volume in comparison to coniferous (Holmström et al., 2017). True scarcity of deciduous trees in our study dataset, which featured no fires in the nemoral zone, likely further affected parameterization of the deciduous vegetation in the model. We expect increased statistical model performance with the use of soon to be available SLU Forest Maps 2020, which will have both improved accuracy and enhanced spatial resolution. The SLU Forest Maps we used can also be integrated into Heureka, a widely used decision support system for forestry operations in Sweden (Lämås et al., 2023). This existing integration should greatly facilitate development of a fire risk management module for this system to address projected increases in forest fire risks in the Nordic region (Krikken et al., 2021).

CRediT authorship contribution statement

Sara Sharon Jones: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Maksym Matsala:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Emily Viola Delin:** Writing – review & editing, Data curation, Conceptualization. **Narayanan Subramanian:** Writing – review & editing, Data curation. **Urban Nilsson:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Emma Holmström:** Writing – review & editing, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Igor Drobyshev:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Igor Drobyshev reports financial support was provided by Swedish Research Council Formas. Urban Nilsson reports financial support was provided by Swedish Research Council Formas. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2024.110942.

Data availability

Fire Map 2016–2022 published on Zenodo

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