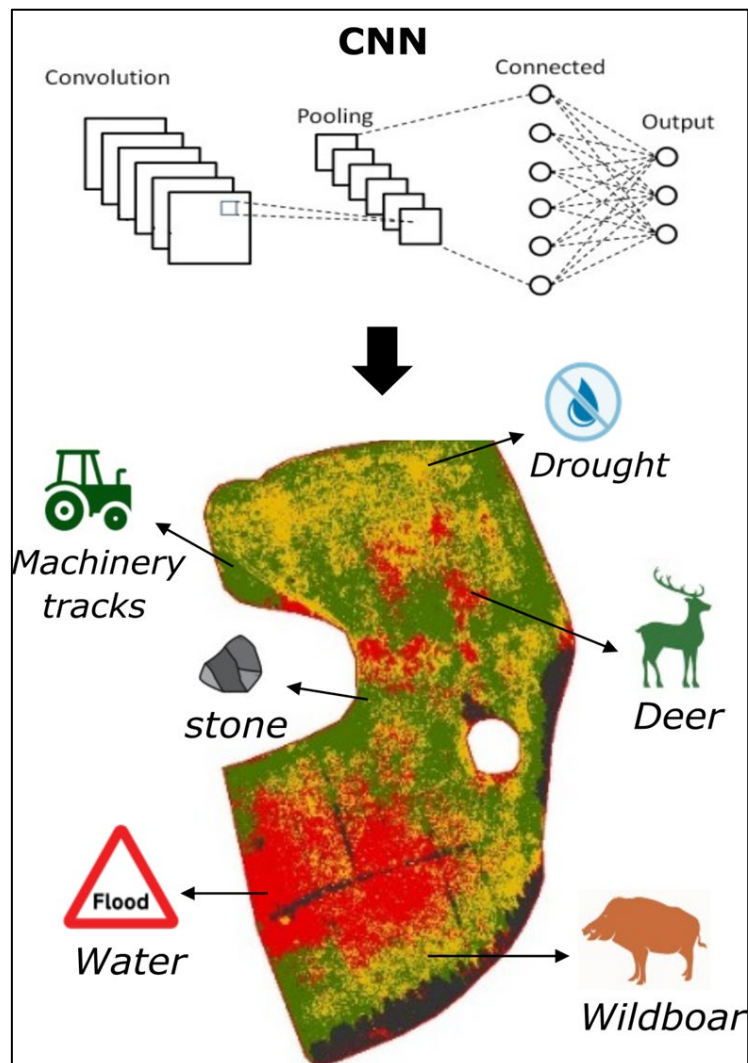


# Deep Learning with CNNs for Classifying Damage Type in Wheat and Grasslands

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Yrsa Kleijkers, Florent Rumiano, Arvid Norström & Petter Kjellander





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# Content

<b>Abstract .....</b>	<b>6</b>
<b>Svensk sammanfattning.....</b>	<b>7</b>
<b>1. Introduction .....</b>	<b>8</b>
1.1 Why a Convolutional Neural Network?.....	8
1.2 What is a CNN?.....	9
1.3 Transfer learning on a CNN.....	9
1.4 Workflow: CNN model creation for damage type classification.....	10
2.1 Data collection 2023 .....	13
2.2 Data collection 2024 .....	15
<b>3. Method .....</b>	<b>17</b>
3.1 Preprocessing.....	17
3.1.1 Image creation .....	18
3.1.3 Image preparation: Augmentations & 10 Dataset creation.....	23
3.2 Hyperparameter Tuning.....	24
3.2.1 Tuning: Main Parameters .....	25
3.2.2 Fine-tuning: Batch Normalization.....	26
3.3 Model Fitting.....	27
3.3.1 10 Dataset Model Fitting .....	27
3.3.2 Full Dataset Model Fitting .....	28
3.3.3 Wheat/Grass Dataset Model Fitting.....	29
3.4 Model Evaluation .....	30
3.4.1 Evaluation Model: Validation Polygons .....	30
3.4.2 Evaluation Model: Full Field Prediction .....	31
<b>4 Results .....</b>	<b>34</b>
4.1 Validation polygons evaluation results.....	34
4.2 Field Prediction Evaluations .....	36
4.3 Post-classification analysis – Damage type ratios .....	39
4.3.1 Wheatlands Jönköping.....	39
4.3.2 Grasslands Jönköping.....	39
<b>5. Limitations and recommendations.....</b>	<b>40</b>
5.1 Limitations: .....	40
5.1.1 Data:.....	40
5.1.2 Model design:.....	40

5.1.3 Model validation: .....	41
5.2 Recommendations: .....	41
5.2.1 Data:.....	41
5.2.2 Model design:.....	41
<b>6. Developed scripts and user guide .....</b>	<b>42</b>
6.1 The developed scripts and required data folder structure .....	42
6.2 Developed scripts overview and descriptions.....	44
6.3 Estimated running times of the developed scripts .....	49
<b>7. Extra, Running times:.....</b>	<b>51</b>
<b>8. References.....</b>	<b>56</b>
<b>Appendix 1: <i>Increasing Data Accuracy Prospect</i>.....</b>	<b>57</b>
<b>Appendix 2: <i>Results - Grass-fitted Model</i> .....</b>	<b>67</b>
<b>Appendix 3: <i>Results - Wheat-fitted Model</i> .....</b>	<b>108</b>
<b>Appendix 4: <i>Results - Fulldata-fitted Model</i> .....</b>	<b>147</b>

# Abstract

Wildlife causes significant economic losses to Swedish agriculture through their feeding behaviour in crops. Accurately assessing these losses is crucial for developing mitigation strategies and reducing conflicts between stakeholders. However, traditional ground-based surveys are labour-intensive, observer-dependent, spatially limited, and not easily scalable. Advances in remote sensing and artificial intelligence (AI) offer new opportunities for automatised to semi-automatized damage detection and mapping at very-high spatial resolution scale.

In this study, we developed a deep learning approach based on Convolutional Neural Networks (CNNs) applied to UAV-derived orthomosaics to discriminate between damage types. The workflow integrated four key steps: preprocessing UAV imagery into normalized image tiles and structured datasets; optimizing model behaviour through hyperparameter tuning; training the CNN with transfer learning, where dense layers were fitted to labelled damage data while convolutional layers remained frozen; and evaluating model performance with independent test sets.

Performance metrics, including accuracy, precision, recall, and F1-score, demonstrated clear differences between wheat and grasslands, as well as between training strategies. In general, models trained on crop-specific datasets outperformed those trained on the full dataset, highlighting the importance of tailoring training data to individual crop types. Across both crops, the no-grid approaches consistently achieved stronger results than grid-based models, suggesting that preserving spatial context improves classification performance. Wheat models benefited more strongly from crop-specific training, showing a pronounced gain in classification reliability compared to grasslands, where improvements were present but more moderate. When applied to full-field predictions, performance declined compared to validation polygons, indicating challenges in generalizing from controlled validation areas to more heterogeneous field conditions.

Overall, the observed trends confirm that CNN-based approaches can capture relevant spectral and spatial features for damage type discrimination, with wheat classifications being particularly sensitive to training data design and quantity. These findings demonstrate the potential of CNN-based methods for UAV-assisted monitoring of crop damage and provide a foundation for scalable and semi-automatized applications in precision agriculture.

## Svensk sammanfattning

Vilt orsakar betydande ekonomiska förluster i svenskt jordbruk genom sitt bete och beteende i grödor. En rättvisande bedömning av dessa förluster är avgörande för att utveckla skadeförebyggande åtgärder och minska konflikter mellan olika intressenter. Traditionella fältinventeringar är dock arbetskrävande, observatörsberoende, geografiskt begränsade och svåra att skala upp. Framsteg inom fjärranalys och artificiell intelligens (AI) öppnar nya möjligheter för semi-automatiserad eller helt automatiserad skadekartering med mycket hög rumslig upplösning.

I denna studie utvecklade vi en djupinlärningsmetod baserad på konvolutionella neurala nätverk (CNN) tillämpad på UAV-baserade (drönar-baserade) ortomosaiker för att skilja mellan olika skadetyper. Arbetsflödet, som här beskrivs i detalj, integrerade fyra huvudsteg: (1) förbehandling av UAV-bilder till normaliserade bildrutor och strukturerade dataset, (2) optimering av modellens beteende genom hyperparameterkalibrering, (3) träning av CNN med sk. "transfer learning", där täta bild-lager anpassades till verifierade skador medan de konvolutionella lagren hölls konstanta, samt (4) utvärdering av modellprestanda med oberoende testdata.

Mått på modellprestanda som noggrannhet (accuracy), precision, återkallningsgrad (recall), och F1-värde visade tydliga skillnader mellan vete och gräsmarker samt mellan olika modellträningsstrategier. Generellt presterade modeller tränade på grödospecifika dataset bättre än de som tränades på hela datasetet i hopslaget, vilket understryker vikten av att anpassa träningsdata till enskilda grödor. För båda grödorna gav icke-rutbaserade (no-grid) metoder konsekvent bättre resultat än rutbaserade (grid), vilket tyder på att bibehållen rumslig kontext, (ex. biogeografiskt område) förbättrar klassificeringsprestanda. Särskilt vetemodellerna gynnades av grödospecifik träning och visade tydliga förbättringar i klassificeringssäkerhet, medan förbättringarna för gräsmarker var mer måttliga. Vid tillämpning på hela fält sjönk prestandan jämfört med valideringspolygoner, vilket pekar på ett fortsatt utvecklingsbehov för att med än högre precision kunna generalisera från kontrollerade valideringsområden till mer heterogena fältförhållanden.

Sammantaget bekräftar resultaten att CNN-baserade metoder kan fånga relevanta spektrala och rumsliga egenskaper för att skilja mellan olika skadetyper, medan klassificeringen i vete är särskilt känslig för träningsdatans utformning och omfattning. Dessa resultat visar dessutom potentialen för CNN-baserade metoder vid UAV-assisterad övervakning av grödskador och lägger grunden för skalbara och semi-automatiserade tillämpningar inom precisionsjordbruk.

# 1. Introduction

A deep learning approach using Convolutional Neural Networks (CNNs) has been developed to automate the classification of a limited number of specific individual agricultural damage instances in damage classification maps according to their underlying cause, hereafter referred to as the *damage type*, detailed in section 2. Given the data-intensive nature of CNNs, the architecture was designed to be scalable and robust, with the aim of incrementally improving classification performance as additional annotated data becomes available over time.

Subsequent subsections delineate the conceptual and functional differences between CNNs and the previously employed machine learning models—Random Forest (RF) and Support Vector Machine (SVM)—which were used for binary damage classification (i.e., damage vs. no-damage) in the generation of damage maps (Kjellander et al. 2024). The rationale for employing a deep learning model for damage type classification, as opposed to conventional machine learning models, is also discussed.

In addition, this section provides a concise theoretical overview of CNNs, with particular attention to their applicability in spatial pattern recognition tasks common in ecological remote sensing. It further elaborates on the integration of transfer learning strategies within the CNN architecture to leverage pre-trained feature representations, and outlines the end-to-end pipeline encompassing model architecture design, training procedures, and performance evaluation.

## 1.1 Why a Convolutional Neural Network?

A Convolutional Neural Network (CNN) is a type of deep learning model that differs fundamentally from the machine learning models previously used for binary damage classification—namely, Random Forest (RF) and Support Vector Machine (SVM). One of the key distinctions between traditional machine learning and deep learning approaches lies in feature engineering. Machine learning models depend heavily on manually selected input features—such as vegetation indices or texture metrics derived from UAV imagery—that are chosen based on domain knowledge and assumptions about what might be informative for classification.

In contrast, deep learning models like CNNs learn to extract relevant features automatically from raw input data, without requiring predefined inputs. Through multiple layers of convolutional filters, CNNs can detect spatial patterns of increasing complexity, enabling them to learn nuanced, high-level representations directly from image data. This property makes CNNs particularly well-suited for analysing complex spatial data such as orthomosaics derived from UAV multispectral imagery, where damage signatures can vary in shape, texture, wave lengths, scale, and context.

Given the inherent complexity and variability within and between damage types in UAV-acquired imagery, as well as the need for robust and generalizable models that can adapt to new data in future monitoring scenarios, a deep learning approach was deemed more appropriate. The use of a CNN allows for more flexible and scalable classification of damage types, without the need for exhaustive manual feature design or task-specific preprocessing.



## 1.2 What is a CNN?

Convolutional Neural Networks (CNNs) are a class of deep learning models introduced in the late 1990s (LeCun et al. 1998) and have since become the cornerstone of image analysis in computer vision. CNNs are specifically designed to process data with a grid-like topology, such as digital images, by learning spatial hierarchies of features through layered transformations.

A CNN is composed of two main components (Figure 1). The first component is a sequence of *convolutional layers* responsible for automatic feature extraction. These layers are organized hierarchically: the early layers detect low-level features such as edges, corners, and textures, while deeper layers capture more abstract, high-level patterns relevant to the task at hand (e.g., the distinct imprint of a vehicle tire in a damaged crop field). The hierarchical structure allows the model to present increasingly complex spatial information.

The second component of a CNN is a *fully connected (dense) neural network*, which performs classification based on the features extracted by the convolutional layers. This dense network is trained to assign the input data to one of several predefined classes—in this case, a limited number of different types of crop damages. By learning the mapping between feature representations and damage categories, the model can automatically infer the likely cause of damage based on spatial patterns present in the UAV imagery.

## 1.3 Transfer learning on a CNN

Convolutional Neural Networks (CNNs), while powerful, typically require large amounts of labelled training data to effectively learn the parameters of both their convolutional and fully connected (dense) layers. In the context of this study, labelled data refers to UAV imagery of damaged parts of variable size and origin in agricultural fields paired with in-field-verified annotations specifying the cause of each specific damage. Compared to machine learning models such as Random Forest (RF) and Support Vector Machine (SVM), CNNs involve more trainable parameters, primarily due to their multiple convolutional layers and learnable filters, which makes them considerably more data-demanding during training.

Given the limited amount of annotated training data currently available, we adopted a *transfer learning* approach to enable the use of CNNs for damage-type classification. Transfer learning is a widely used technique in deep learning where a model trained on a large, generic dataset is repurposed for a different but related task. Specifically, we utilized CNN architectures whose convolutional layers had already been pre-trained on large-scale image classification tasks. These layers were then used to extract features from our UAV imagery of agricultural grassland and wheat fields.

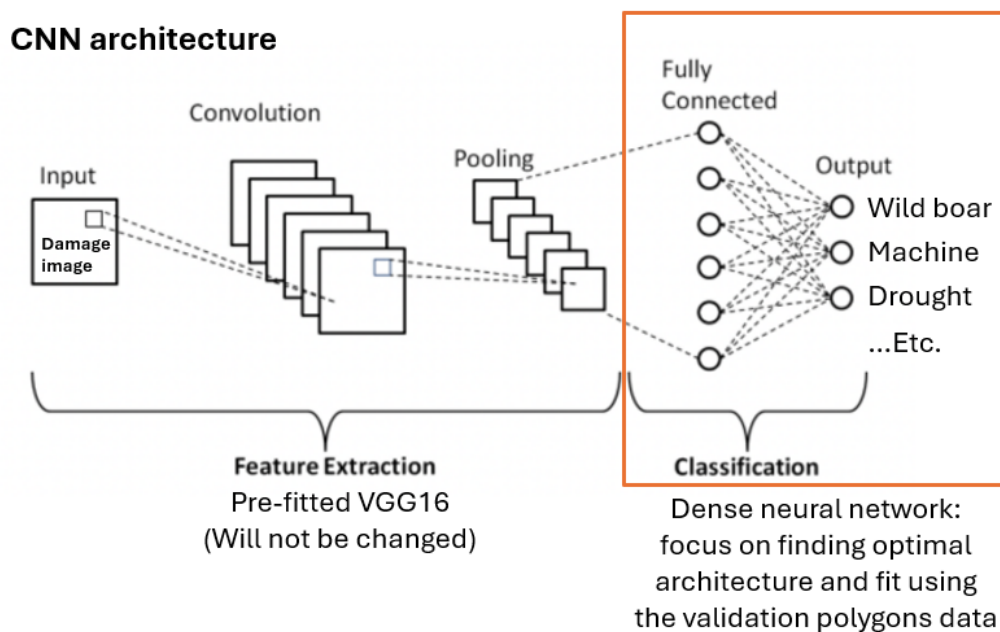
In this approach, only the *dense (classification) layers* of the network were trained using annotated data (i.e., damage-type labels), while the convolutional layers remained fixed during training (Figure 1). This greatly reduces the number of parameters that need to be optimized and thus lowers the demand for extensive labelled data, making it feasible to train effective models even in data-constrained ecological settings.

We explored several well-established CNN architectures with pre-trained convolutional layers, including ResNet (He et al. 2015), DenseNet (Huang et al. 2016), Inception (Szegedy et al. 2015), Xception-V3 (Chollet, 2016), InceptionResNet (Szegedy et al. 2016), and VGG16 and VGG19

(Simonyan & Zisserman, 2014). All these models were originally trained on the ImageNet dataset (Deng et al. 2009), a publicly available benchmark containing approximately 15 million labelled natural images across thousands of categories.

Among the tested architectures, the VGG16 model demonstrated the best classification performance on our dataset, while also offering a relatively simple and interpretable convolutional structure. For this reason, we selected the VGG16 architecture for our final model. Originally developed by Simonyan and Zisserman at the University of Oxford for the 2014 ImageNet Large Scale Visual Recognition Challenge (Russakovsky et al. 2015), VGG16 consists of 13 convolutional layers followed by 3 dense layers.

In summary, by leveraging transfer learning, the convolutional layers of the VGG16 model—pre-trained on ImageNet—were reused as fixed feature extractors, and only the dense layers (Figure 1) were retrained using labelled damage-type data collected through field surveys (hereafter referred to as *validation polygons*). This approach enabled the application of CNNs despite limited training data, while still achieving high classification performance.



**Figure 1.** General architecture of the Convolutional Neural Network (CNN) used for damage-type classification. The model architecture is divided into two components: (1) convolutional layers, which perform automated feature extraction and were pre-trained on a large external dataset (ImageNet); and (2) a dense neural network, which was constructed and trained using field-validated data (referred to as *validation polygons*) specific to this study. Transfer learning was applied by freezing the weights of the convolutional layers during training, allowing only the dense layers to be optimized. This approach reduces the need for large labelled datasets while maintaining strong classification performance. Figure adapted from Pal & Mishra (2023).

## 1.4 Workflow: CNN model creation for damage type classification

An overview of the complete workflow used to develop the CNN model for damage-type classification is illustrated in Figure 2. As previously discussed, (Section 1.3), the primary focus during model development was on designing and fitting the *dense neural network* component,

while the convolutional layers—used for automated feature extraction—remained fixed as part of the transfer learning approach (Figure 1).

The workflow consists of four main components: 1. Preprocessing, 2. Hyperparameter Tuning, 3. Model Fitting, 4. Model Evaluation

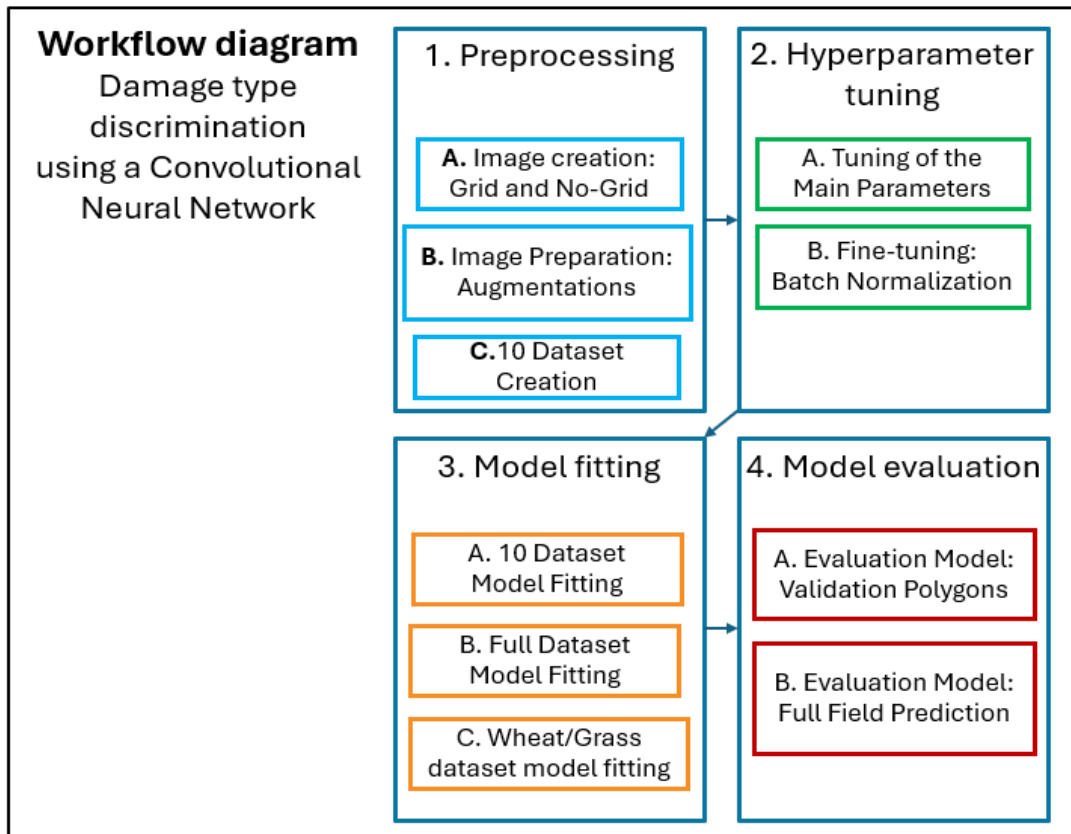
1. Preprocessing involved the preparation of input data, including the generation of image tiles from UAV orthomosaics, image normalization, and the organization of the dataset into training, validation, and testing sets. These datasets formed the input pipeline for both tuning and training the CNN models.

2. Hyperparameter tuning was performed to optimize model-specific settings that are not learned during training but must be specified by the user—such as learning rate, number of dense units, batch size, dropout rate, and choice of activation function. This step is critical in deep learning models, as hyperparameters can substantially impact model performance.

3. Model fitting involved training the dense layers of the CNN using the labelled dataset produced during preprocessing. During this phase, the network learned to associate extracted features from UAV images with the correct damage type labels (e.g., wild boar vs. drought damage). The convolutional layers remained frozen throughout this process, as defined by the transfer learning protocol.

4. Model evaluation assessed the performance of the trained CNN using a withheld test set, allowing an objective estimate of classification accuracy, robustness, and generalization capacity. Metrics of model performance such as accuracy, precision, recall, and F1-score were computed to evaluate the model's effectiveness in distinguishing between damage types.

Each of these components contains several sub-processes (denoted A–C in Figure 2), which are explained in detail in section 3.



**Figure 2.** Overview of the workflow used to develop the CNN for damage-type classification. The process is divided into four main stages: 1) **Preprocessing**, 2) **Hyperparameter Tuning**, 3) **Model Fitting**, and 4) **Model Evaluation**. Each stage contains multiple sub-components (denoted A–C), which are detailed in Section 3 (Methodology). The workflow reflects the transfer learning approach, where convolutional layers are pre-trained and remain static, while only the dense neural network is constructed and trained using field-validated data.

## 2. Data description

The labelled data used for training and evaluating the convolutional neural network (CNN) models consisted of manually digitized Global Navigation Satellite System (GNSS) points collected during field surveys. Each GNSS point marked the presence a of crop damages of a specific origin (e.g., wild boar, deer, drought), as observed on-site by three different qualified observers. During post-processing, these points served as ground control for manually digitizing polygons delineating observed damaged areas, using high-resolution RGB orthomosaics from UAV imagery as visual reference. Each resulting polygon, hereafter referred to as a *validation polygon*, retained the damage type information from its corresponding GNSS point. These validation polygons were utilized in two key stages of model development: hyperparameter tuning (see Section 3.2) and model evaluation (see Section 3.4).

Notably, in the 2023 field campaign, the classification of damage types was open-ended and recorded based on field observations without a predefined taxonomy. By contrast, the 2024 survey adopted a standardized list of damage categories, which included:

1. Wild boar	4. Wildlife trails	7. Machine	10. Lay
2. Badger	5. Drought	8. No seed	11. Wells
3. Deer	6. Water	9. Rock	12. Other

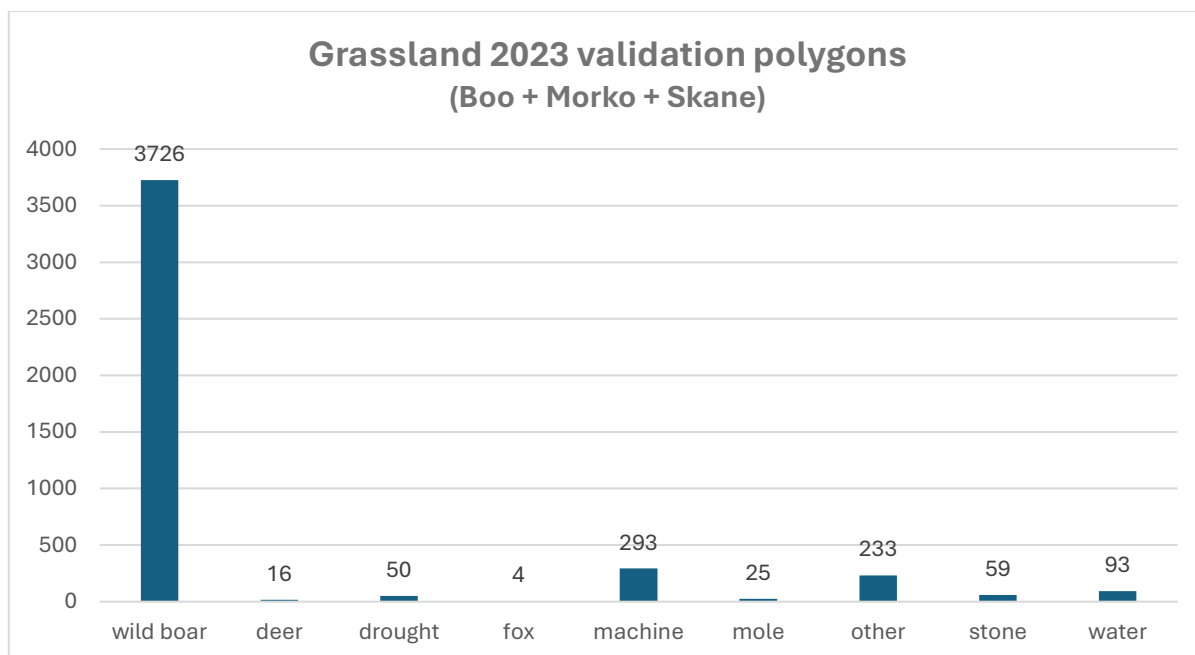
### 2.1 Data collection 2023

In the field season of 2023, three agricultural areas in southern Sweden known to suffer from high levels of wildlife damages were surveyed. These areas were situated on three different estates: in the very south Christinehof (Skåne), Boo in south central Sweden and Hörningsholm (Mörkö) in southeastern Sweden. The number of “collected” GNSS locations used as reference for the digitalization of validation polygons varied considerably (0 – 1545 instances) between areas, crop type (grasslands or wheat) and damage classes (Tables 1 and 2; Figure 3 and 4).

#### 2.1.1 Grassland 2023 (Boo, Mörkö, Skåne)

**Table 1.** Number of validation polygons per damage type and study area for grasslands in Boo, Mörkö, and Skåne during the 2023 field season. The last row summarizes the total number of polygons reported per damage type across all study areas.

	<b>Wild</b>								
	<b>boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Fox</b>	<b>Machine</b>	<b>Mole</b>	<b>Other</b>	<b>Stone</b>	<b>Water</b>
<b>Boo</b>	937	16	29	1	31	0	104	23	11
<b>Mörkö</b>	1545	0	21	0	38	0	129	13	82
<b>Skåne</b>	1244	0	0	3	224	25	0	23	0
<b>Total</b>	3726	16	50	4	293	25	233	59	93



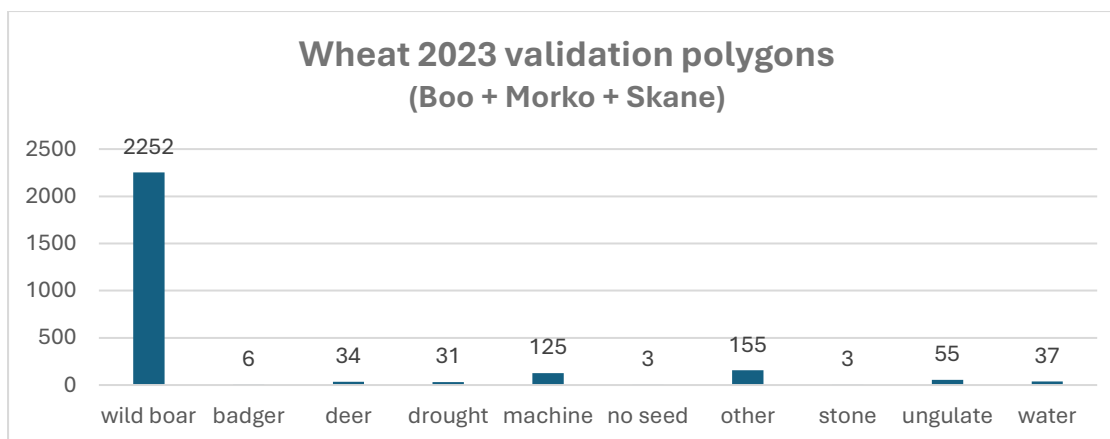
**Figure 3.** Distribution of the validation polygons created per damage type for the grasslands of Boo, Mörkö, and Skåne in 2023. The number indicates the available amount of digitized validation polygons.

### 2.1.2 Wheatland 2023 (Boo, Morko, Skane)

Pay attention to the fact that different damage types are present.

**Table 2.** Distribution of validation polygons per damage type for grassland sites in Boo, Mörkö, and Skåne during the 2023 field season. The numbers indicate the total count of digitized validation polygons available for each damage type. The last row summarizes the total number of polygons reported per damage type across all study areas.

	Wild boar	Bad- ger	deer	droug ht	machine	No seed	other	stone	Ungu- late	water
<b>Boo</b>	609	0	13	29	89	3	124	1	55	11
<b>Mörkö</b>	808	6	21	2	36	0	30	2	0	26
<b>Skåne</b>	835	0	0	0	0	0	1	0	0	0
<b>Total</b>	2252	6	34	31	125	3	155	3	55	37



**Figure 4.** Distribution of the validation polygons created per damage type for the wheatlands of Boo, Mörkö, and Skåne, 2023.

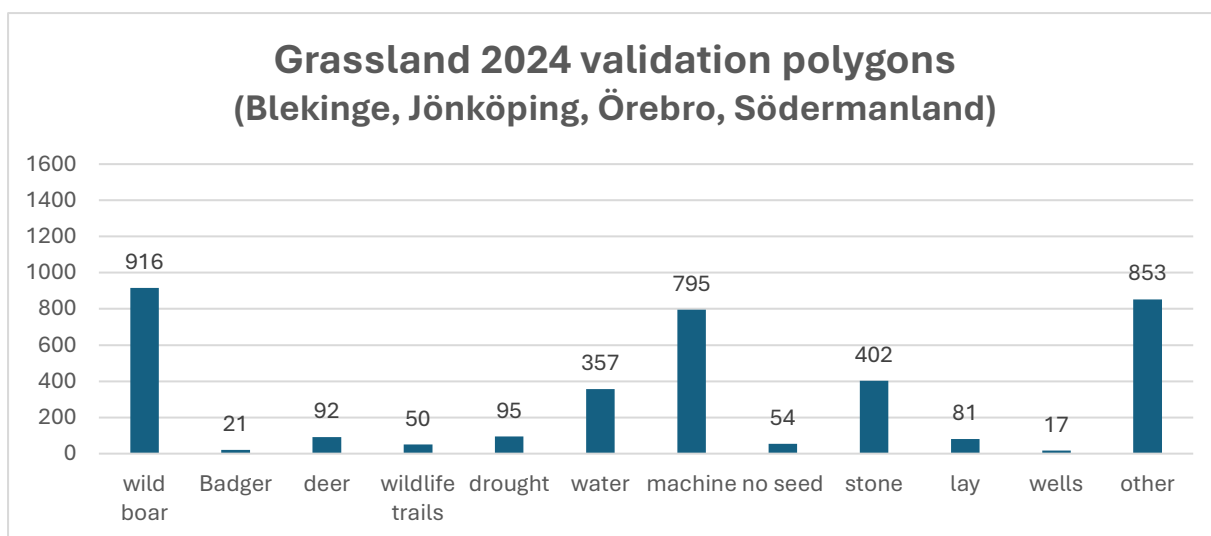
## 2.2 Data collection 2024

Tables 3 and 4 summarize the number of validation polygons collected in 2024 for grassland (see Section 2.2.1) and wheat (see Section 2.2.2), respectively. Each table presents both the total number of validation polygons and their distribution across the different study areas. Complementing this information, Figures 5 and 6 provide spatial visualizations of the validation polygon distribution for grassland and wheat sites, respectively, highlighting their geographic extent within each study area. It is important to note that, similarly to the 2023 survey, the number of “collected” GNSS locations used as reference for the digitalization of validation polygons varied considerably (0 – 559 instances) between areas, crop type (grasslands or wheat) and damage classes (Tables 3 and 4; Figure 5 and 6).

### 2.2.1 Grassland 2024 (Blekinge, Jönköping, Örebro, Södermanland)

**Table 3.** Number of validation polygons per damage type and study area for grasslands in Blekinge, Jönköping, Örebro, and Södermanland during the 2024 field season. The last row reports the total number of validation polygons recorded for each damage type across all study areas.

	Wild boar	Bad -ger	Wild -life deer	Wild -life trails	Drought	Water	Machi ne	No seed	Stone	lay	wells	Other
<b>Blekinge</b>	127	21	0	0	19	18	72	3	157	0	1	56
<b>Jönköping</b>	436	0	0	5	53	81	341	14	140	0	0	529
<b>Örebro</b>	188	0	65	18	9	144	226	33	47	61	9	139
<b>Söderma nland</b>	165	0	27	27	14	114	156	4	58	20	7	129
<b>Total</b>	916	21	92	50	95	357	795	54	402	81	17	853



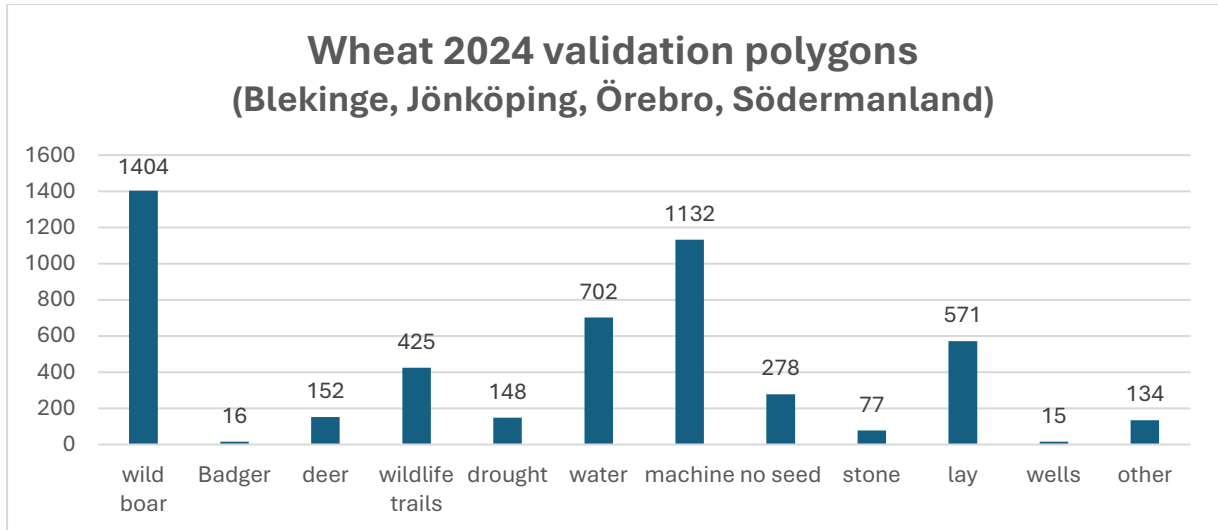
**Figure 5.** Distribution of validation polygons per damage type for agricultural grasslands in Blekinge, Jönköping, Örebro, and Södermanland during the 2024 field season.

#### 2.2.2 Wheat 2024 (Blekinge, Jönköping, Örebro, Södermanland)

**Table 4.** Number of validation polygons per damage type and study area for wheat fields in Blekinge, Jönköping, Örebro, and Södermanland during the 2024 field season. The last row indicates the total number of validation polygons recorded for each damage type across all study areas.

	Wild boar	Bad -ger	deer	Wild -life trails	drought	water	Machi ne	No seed	Stone	lay	wells	Other
<b>Blekinge</b>	261	1	9	41	106	315	350	67	19	18	4	48
<b>Jönköping</b>	468	15	12	97	22	123	375	59	49	114	15	66
<b>Örebro</b>	559	0	102	235	19	153	368	117	3	422	3	19
<b>Söderma nland</b>	116	0	29	52	1	111	39	35	6	17	2	1
<b>Total</b>	1404	16	152	425	148	702	1132	278	77	571	15	134





**Figure 6.** Distribution of validation polygons per damage type for agricultural wheatlands in Blekinge, Jönköping, Örebro, and Södermanland during the 2024 field season.

### 3. Method

This section provides detailed descriptions of each analysis outlined in the workflow diagram (Figure 2). In total, six convolutional neural network (CNN) models were developed, comprising both grid-based and non-grid-based approaches: (1) grid-based CNN trained on the full dataset, (2) grid-based CNN trained on wheat data, (3) grid-based CNN trained on grassland data, (4) non-grid-based CNN trained on the full dataset, (5) non-grid-based CNN trained on wheat data, and (6) non-grid-based CNN trained on grassland data.

It is important to emphasize that the CNN architectures and hyperparameter settings described in this section were influenced by the limited volume of training data available at this stage of the project. The models were restrained and designed to classify a limited number of six specific damage types: Deer, Drought, Machine, Stone, Water, and Wild Boar. These classes were selected based on data availability and on request from agriculture/wildlife management at the time of model development, specifically from grassland and wheat surveys in 2023 and grassland surveys in 2024.

As additional data become available in the future—particularly from wheat fields in 2024 and potential inclusion of other damage types—the CNN architectures and parameter configurations will require revision to optimize classification performance. Nevertheless, the methodology and supporting scripts developed in this phase can be reused to guide model refinement and retraining under expanded data conditions.

#### 3.1 Preprocessing

During preprocessing, the validation polygons were used to generate image patches representing damage, which served as input for the CNN models (see Section 1.1). These image

patches underwent data augmentation and were subsequently divided into training, validation, and test subsets to form complete datasets (see Sections 1.2 and 1.3). One dataset was specifically created for hyperparameter tuning (see Section 2), while ten additional datasets were generated to evaluate the stability and robustness of the CNN models (see Section 3.3.1).

### 3.1.1 Image creation

CNNs require all input images to be of uniform dimensions—specifically, identical width, height, and number of channels. To generate such input images, two distinct image creation strategies were explored.

Strategy 1 employed a grid-based approach (Figure 7): grid cells overlapping with validation polygons were used to clip the RGB orthomosaic, resulting in damage-centered image tiles. Strategy 2 (Figure 7) utilized the exact shape of each validation polygon to extract damage-specific image patches directly from the orthomosaic.

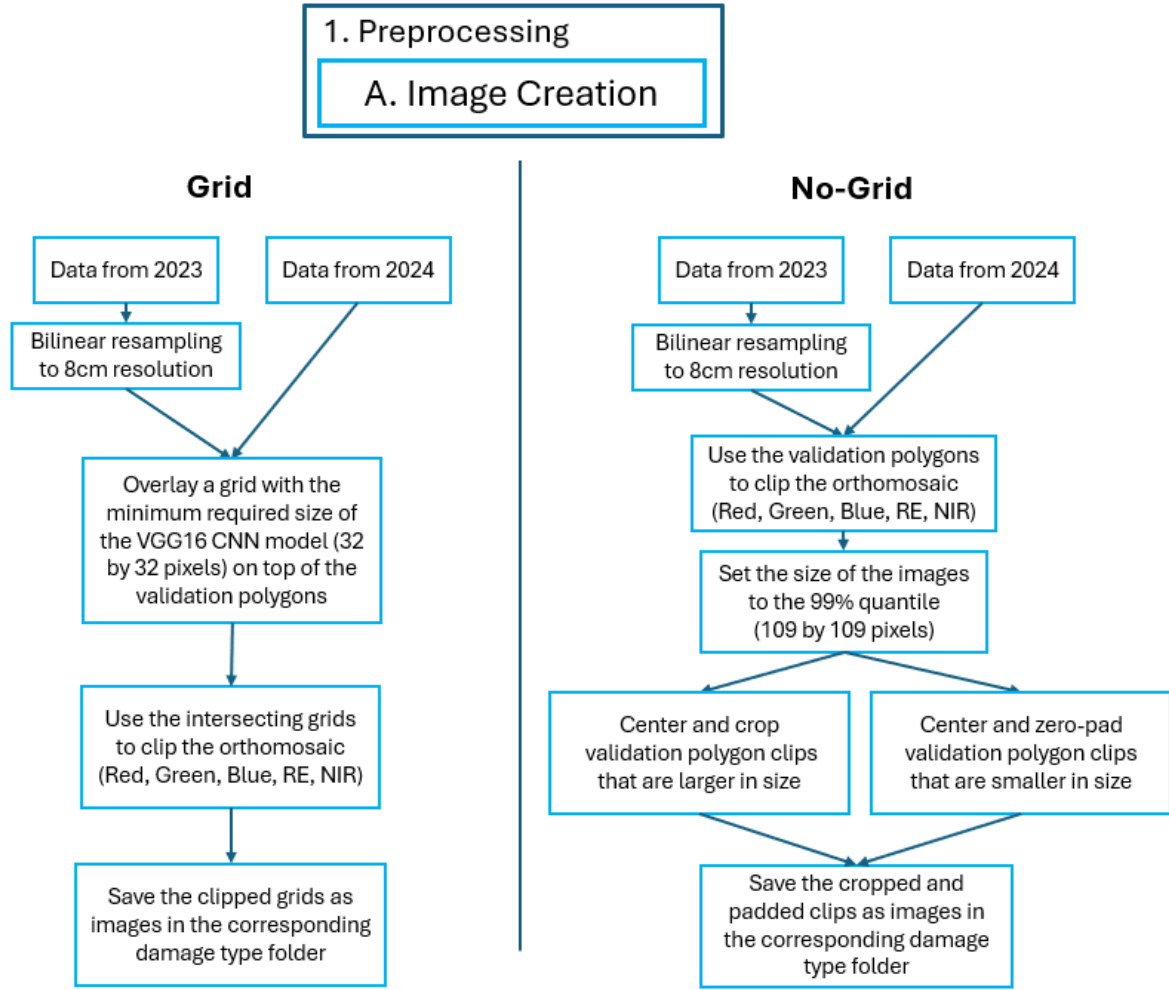
Each strategy necessitated a distinct CNN architecture and independent parameter tuning for the dense (fully connected) layers. This led to the development and evaluation of two separate CNN models per dataset (i.e., full data, wheat-only, or grassland-only; see Section 2), each tailored to the respective input image creation method.

The rationale for investigating both approaches stems from their respective advantages and limitations. Strategy 2 (no-grid) is hypothesized to be more favourable for classification performance, as it preserves the full shape of the damaged area—an important spatial feature. However, applying this strategy to model predictions (i.e., post-classification damage maps) is highly complex. When damage regions are connected and potentially consist of multiple damage types, it becomes infeasible to accurately reconstruct polygon boundaries (see section 3.4.2 for details).

In contrast, Strategy 1 (grid-based) allows for straightforward integration with the damage maps, since any grid cell intersecting a predicted damaged area can be directly used as an input image. This simplifies post-classification workflows and avoids ambiguities related to boundary delineation. However, the trade-off is that grid-based images may include background or incomplete damage areas, potentially reducing classification accuracy due to occlusion and noise.

Given these trade-offs, both strategies were systematically evaluated to determine their impact on the CNNs' ability to classify damage types.

Finally, due to a change in spatial resolution of the RGB orthomosaics between years (5x5 cm in 2023 and 8x8 cm in 2024) the 2023 data were resampled using bilinear interpolation to match the 8x8 cm resolution prior to image generation (Figure 7).



**Figure 7.** The steps of the analysis of 1. Preprocessing - A. Image creation subcomponent for strategy 1. No-grid and strategy 2. Grid.

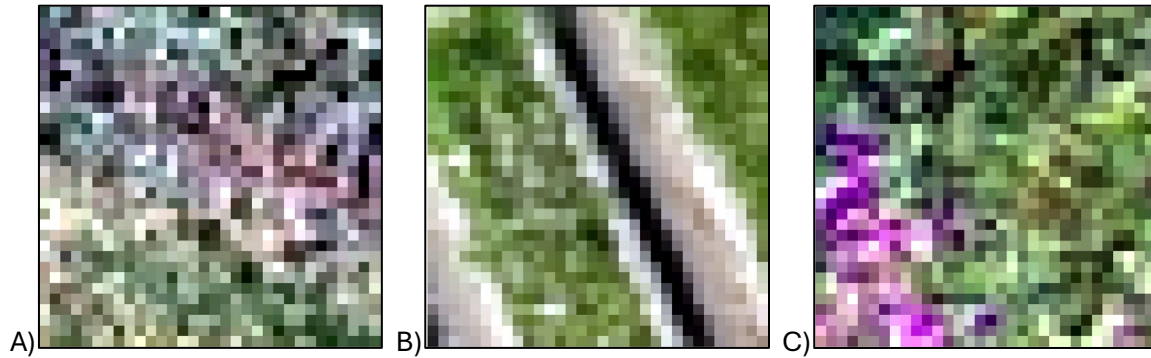
### Strategy 1: Grid Image Creation

Strategy 1 for image creation involved applying a grid overlay to the validation polygons, with illustrative examples (Figure 8). The number of images generated using this method across grasslands and wheat fields in 2023 and 2024 varied considerably and between 3 and 22,951, depending on year, crop and damage class (Table 5).

Each grid cell that intersected a validation damage polygon was used to clip the RGB orthomosaic, producing a candidate image for CNN input. In instances where a grid cell overlapped with two or more validation polygons of different damage types, the image was assigned the label corresponding to the polygon with the largest proportional area. If three or more damage types were present in a single cell, the cell was labeled as “mixed” to reflect this ambiguity.

The initial grid cell size was set to  $18 \times 18$  pixels, corresponding to the 75th percentile size of the validation damage polygons. This size was selected to minimize cases where multiple damage types would appear in the same image. Furthermore, CNNs are known to be relatively robust in handling partially visible objects (e.g., when a damage polygon is split across adjacent grid cells) and in scenarios where a large portion of the image contains background.

However, due to architectural constraints of the VGG16 convolutional neural network used in this study (refer to Subsection 1.3), the input image size was subsequently increased to  $32 \times 32$  pixels. This change was necessary to accommodate the multiple down-sampling operations, such as max pooling, performed within VGG16's convolutional layers (Simonyan & Zisserman, 2014), which require a minimum input resolution to function properly.



**Figure 8.** Example input images ( $32 \times 32$  pixels) generated from validation damage polygons using Strategy 1 – Grid-based image creation. A) Image derived from a polygon labelled as Water damage. B) Image derived from a polygon labelled as Machine damage. C) Image derived from a polygon labelled as Wild boar damage. Each image corresponds to a grid cell intersecting a single validation polygon, clipped from the RGB orthomosaic.

**Table 5.** Total number of created grid images based on the 2023 and 2024 wheat and grassland surveys.

	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>water</b>	<b>Wild boar</b>
2023 grass	19	949	942	149	592	6577
2023 wheat	285	1173	2274	3	680	6077
2024 grass	347	1329	5166	1029	21918	2673
2024 wheat	782	1990	9593	135	22951	6457
<b>Total</b>	1433	5441	17975	1316	46141	21784

#### **Strategy 2: No-grid Image creation**

Strategy 2 involved generating images by directly using the shape of the validation polygons (examples in Figure 9). The total number of images created using this method for grasslands and wheatlands in 2023 and 2024 is presented in Table 6.

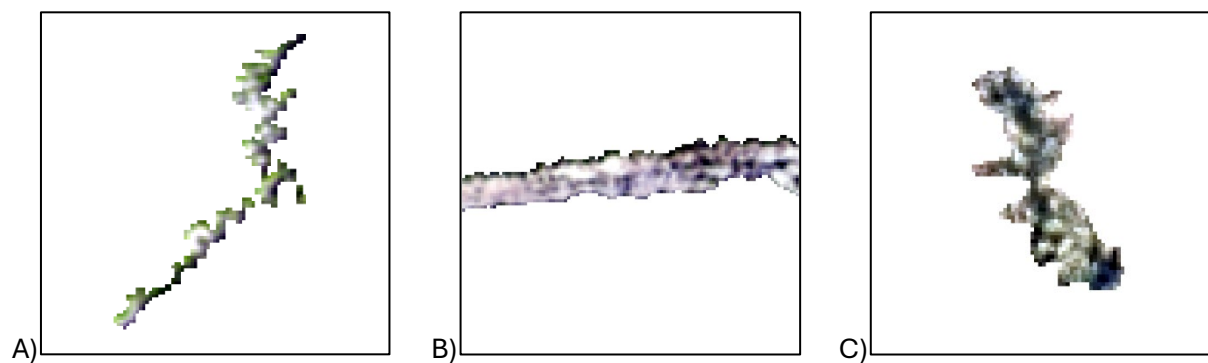
Since the validation polygons vary in spatial extent, and CNNs require uniform input image dimensions (i.e., consistent width, height, and number of channels), a standardized image size

was determined. Validation polygons from 2023 were used to estimate an appropriate size threshold: the 99th percentile polygon had an area of approximately 76 m<sup>2</sup>, meaning that 99% of all validation polygons were smaller than this. Based on the 8 cm spatial resolution of the RGB orthomosaics, this area corresponds to 109 × 109 pixels. This size was thus selected as the fixed input dimension for images created under Strategy 2.

To accommodate variation in polygon sizes while maintaining shape fidelity:

- If polygon width or height was smaller than 109 pixels, it was centered within a 109 × 109 pixels frame and zero-padded to fill the image (Figure 10A and 10C).
- If the polygon exceeded 109 pixels in width or height, it was centered and cropped to the standard size (Figure 10B).

This approach ensured that polygon shapes were not distorted during preprocessing and that relative damage size was retained—both critical considerations when training CNN models to detect and classify damage types.



**Figure 9.** Examples of images (109 × 109 pixels) generated from validation damage polygons using Strategy 2: no-grid image creation. Each image was clipped from the RGB orthomosaic based on the exact shape of a validation polygon and either zero-padded or cropped to maintain a consistent input size for the CNN. A) Image created from a water damage polygon (zero-padded). B) Image created from a machine damage polygon (centered and cropped). C) Image created from a wild boar damage polygon (zero-padded).

**Table 6.** Total number of no-grid images created from the 2023 and 2024 wheat and grassland datasets. One image was generated per validation polygon using Strategy 2 (polygon-based clipping), resulting in image counts that directly correspond to the number of validation polygons available for the selected damage classes.

	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>water</b>	<b>Wild boar</b>
2023 grass	16	50	293	59	93	3726
2023 wheat	34	31	125	3	37	2252
2024 grass	92	95	795	402	357	916
2024 wheat	152	148	1132	77	702	1404
<b>Total</b>	294	324	2345	541	1189	8298

### 3.1.2 Prospect on the required data amount

By fitting the grid- and no-grid-based models with increasing amounts of currently available data, a prospect is created on the required data to reach a specific accuracy by the created CNN models fitted on the fulldata (grass + wheat), wheat and grass data. The available data was split up into increasing sizes of datasets (i.e., 10%, 20%, 30%, ..., 100%). The validation data of the median-performing dataset (subsection 3.3.1) for the grid and no-grid-based CNN models was used to validate the fitting during the training. Table 7 shows the validation data distribution for the full-data, wheat- and grass-fitted model that was used to create these prospects.

**Appendix 1 - Increasing Data Accuracy Prospect** provides the curves of each fulldata, wheat, and grass model fit for the validation accuracy with increasing data. A logarithmic trendline was used to create the prospect on the required amount of data needed.

Summary of results:

**Fulldata-fitted model:**

- Grid: **100 times** more data is required to reach about **78% overall accuracy**.
- No-Grid: **100 times** more data is required to reach about **90% overall accuracy**.

**Wheat-fitted model:**

- Grid: **100 times** more data is required to reach **80% overall accuracy**.
- No-Grid: **10 times** more data is required to reach **90% overall accuracy**.

**Grass-fitted model:**

- Grid: **100 times** more data is required to reach **above 80% overall accuracy**.
- No-Grid: **20 times** more data is required to reach **90% overall accuracy**.

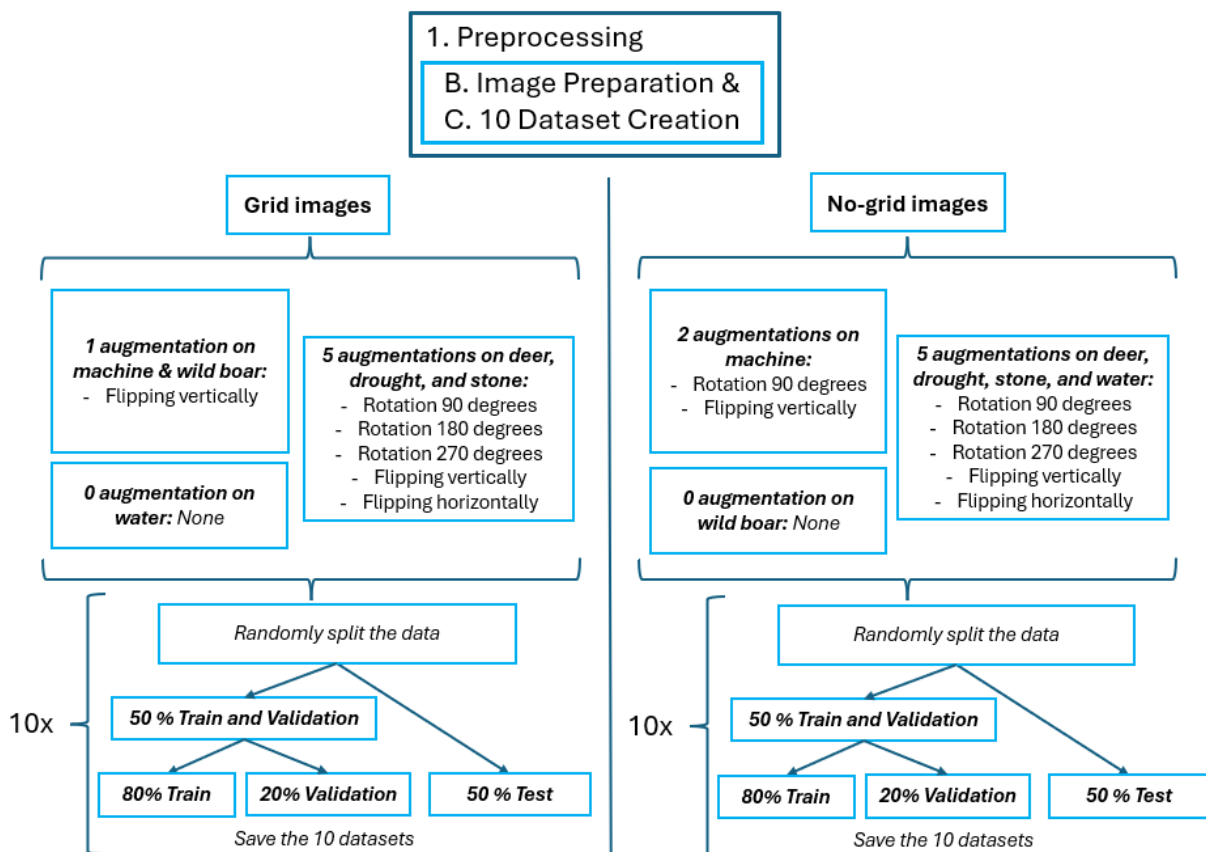
**Table 7.** Data distribution of the validation dataset used to validate the data fittings with the increasing amount of data.

	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>Wild boar</b>
<i>Wheat Grid</i>	643	1867	2323	96	2445	2490
<i>Wheat No-Grid</i>	102	97	399	55	346	380
<i>Grass Grid</i>	89	727	1775	350	6807	2759
<i>Grass No-Grid</i>	75	92	451	251	253	476
<i>Fulldata Grid</i>	843	3317	3584	771	4566	4399
<i>Fulldata No-Grid</i>	178	200	778	325	695	766

### 3.1.3 Image preparation: Augmentations & 10 Dataset creation

Due to the differing amount of images per damage type class, the preparation of the input image data consisted of balancing the image occurrences per damage type. This was done to prevent the model from creating a bias towards predicting damage to be of a specific i.e., high occurring damage type. Augmentations on the original images were performed to create more input images from underrepresented damage types. The augmentations rotation (90, 180, and 270 degrees) and flipping (horizontal and vertical) were decided to be used. See Figure 10 about what augmentations used on what damage types, for both grid and no-grid images. Table 8 show the total amount of available images per damage type after the augmentations.

The created images were 10 times, randomly split up into 50% training and validation data (of which 80% training and 20% validation) and 50% test data. These 10 datasets were used to evaluate the stableness of the best-found CNN model architectures and parameters (see 3.1). The training data was used to fit the CNN models. The validation data was used to evaluate the model fitting by giving an estimation of the model's performance on unseen data. The test data was used to evaluate the fitted model (section 4).



**Figure 10.** Overview of the preprocessing workflow showing steps for B) Image Preparation and C) Creation of 10 datasets. This includes image augmentation (rotation and flipping) applied to balance damage type classes, followed by repeated random splitting of the dataset into training/validation and test sets for robust CNN evaluation.



**Table 8.** Total number of images available per damage type after image preparation, including rotation and flipping augmentations. The images were generated from the 2023 and 2024 wheat and grassland validation polygons.

	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>water</b>	<b>Wild boar</b>
<b>Grid</b>	8598	32646	35950	7896	46141	43568
<b>No-Grid</b>	1764	1944	7035	3246	7134	8298

## 3.2 Hyperparameter Tuning

Once the images were prepared for CNN input (Figure 9 and Figure 10), an exploration of the optimal dense neural network architecture and parameter settings was conducted (Figure 11). A dedicated dataset was used for this hyperparameter tuning.

Manual trial-and-error on the available 2023 wheat and grassland data and 2024 grassland data revealed that the optimal architecture included two dense layers for grid-based images, and two or three dense layers for no-grid images. A learning rate of 0.0001 was selected to balance model convergence with computational efficiency. The Adam optimizer was chosen for its ability to adapt the learning rate during training—enabling exploration early on and refinement later in training (Kingma et al., 2015).

Categorical cross-entropy was used as the loss function, suitable for this multi-class classification problem. ReLU was selected as the activation function for the dense layers to mitigate vanishing gradients and to accelerate convergence compared to traditional functions like Tanh or Sigmoid (Nair and Hinton, 2010).

Training was capped at 300 epochs, with early stopping applied based on the validation loss. If no improvement was seen after 10 epochs, training halted and the model state with the lowest validation loss was retained. Additionally, the learning rate was reduced by 80% (minimum 0.00001) if validation loss plateaued for 5 consecutive epochs, further promoting fine-tuning in the later training stages.

An exploratory analysis was also performed to determine the best set of three input channels. Options included combinations of original bands (Red, Green, Blue, Red Edge, NIR) and derived indices (e.g., NDVI). Ultimately, the use of original Red, Green, and Blue channels yielded the best performance for both grid-based and no-grid-based input images.



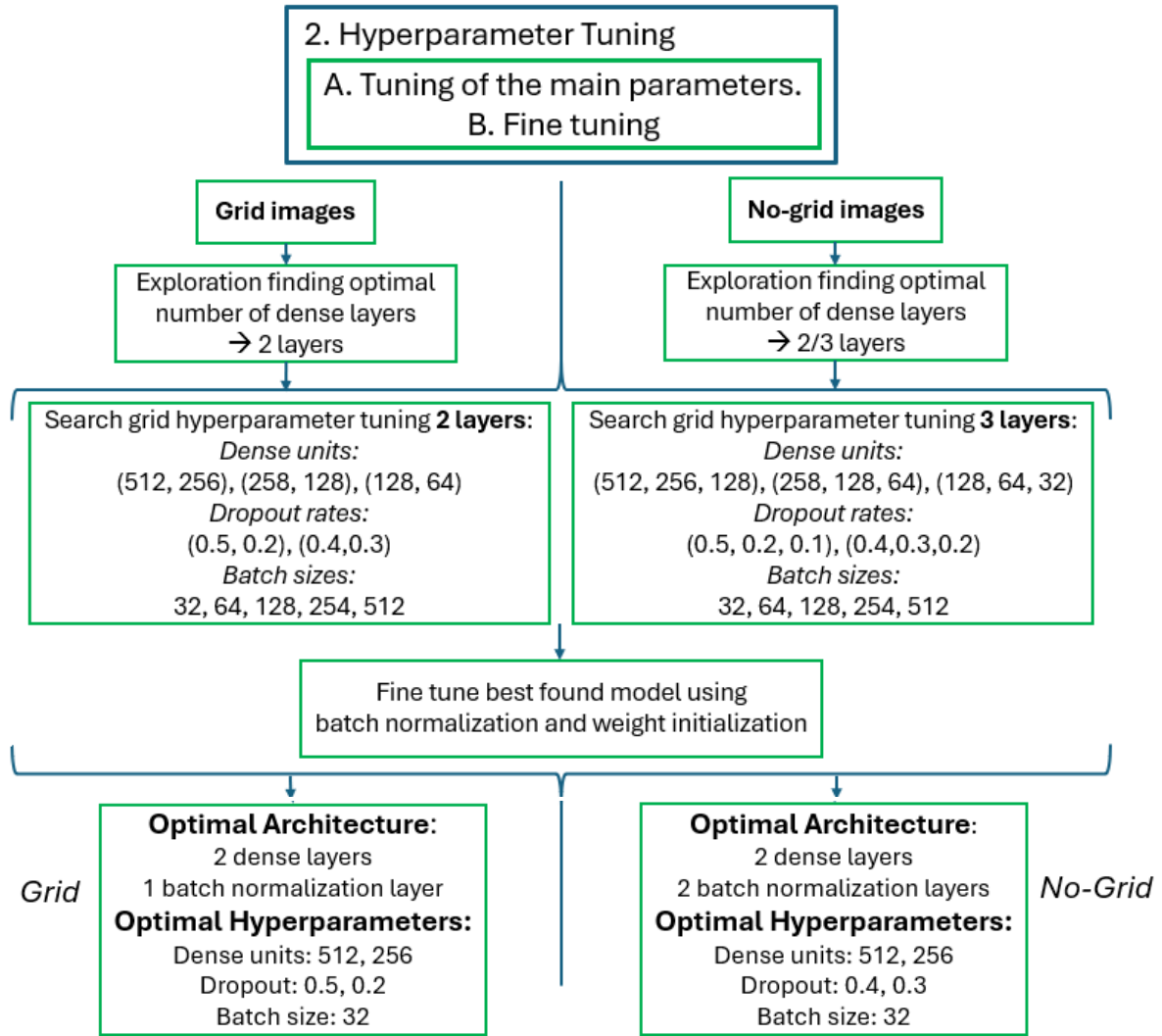


Figure 11: Diagram illustrating the steps involved in hyperparameter tuning, with A. Tuning of the main parameters and B. Fine-tuning of the model.

### 3.2.1 Tuning: Main Parameters

To define the number of dense units, dropout rates, and batch size for the CNN model, hyperparameter tuning was performed (Figure 11). The search grid values for each of these parameters for the dense neural network architectures, with either two (for both grid and no-grid input images) or three (for no-grid input images) dense layers, are shown in Figure 11.

The number of dense units control the complexity of the feature translations (extracted through the VGG16 convolutional layers) into the damage type classification that the dense network can learn. A higher number of units allow the model to learn more complex classification mappings. However, too many units can lead to overfitting, where the model becomes too specialized to the training data and fails to be generalized to new, unseen data. Finding a balance is crucial - having too few units may prevent the model from learning the complexity needed for effective damage type classification, while having too many units may lead to overfitting. To manage this, more units were used in the higher dense layers, which helped narrow down the predictions toward one

of the six different damage types, aligning with the number of units in the final dense layer, equal to the number of classes being predicted.

The dropout rate determines how much of the weights (i.e., parameters) are neglected during each iteration of model training. Dropout is used to prevent overfitting, helping to improve model robustness and generalization to unseen data. However, setting the dropout rate too high can slow down learning, possibly preventing the model from learning the necessary complexity to perform accurate damage type classification. Thus, finding a balance between preventing overfitting and avoiding excessive generalization is important when setting the dropout rate.

The batch size determines how much of the training data is used to update model weight before the error is propagated back. Smaller batch sizes result in the error being averaged over fewer samples, which increases the influence of specific data samples but can also lead to overfitting, especially if underrepresented damage types are not present in the batch. Larger batch sizes reduce the impact of any one data sample but average over more errors, which can decrease the amount of learning per iteration. Choosing the optimal batch size is a trade-off between computational power and ensuring that the model learns the relevant patterns from all damage types.

As the wheat data from 2024 was processed last, in December, the hyperparameter tuning was conducted using the wheat and grassland data from 2023, and the grassland data from 2024. The loss from the validation data was used to determine the optimal parameter settings. Based on the available data, the optimal architecture for grid-based input images was a model with two dense layers: 512 and 256 units, dropout rates of 0.5 and 0.2, and a batch size of 32. For the no-grid-based input images, the optimal architecture also consisted of two dense layers with 512 and 256 units, but with dropout rates of 0.4 and 0.3, and a batch size of 32.

### 3.2.2 Fine-tuning: Batch Normalization

The optimal CNN model architecture and parameters were further fine-tuned by applying batch normalization after the dense layers. Batch normalization helps normalize the data by learning the variance and mean of the training sample batches, which reduces the variation in the data between dense layers. This has the dual benefit of simplifying the learning problem and speeding up the convergence of the model during training.

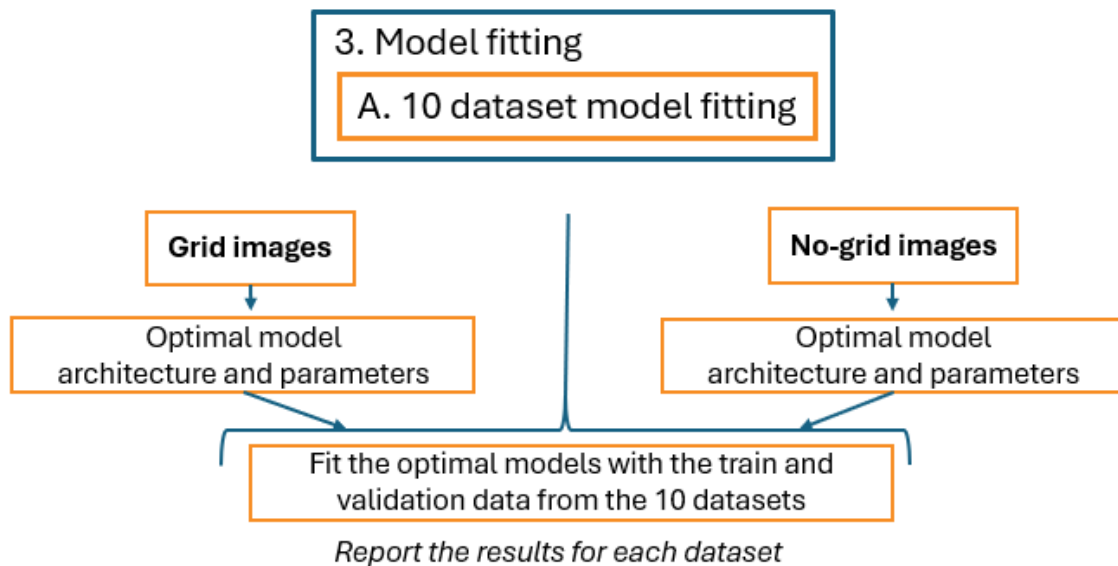
For the grid-based model, the addition of two batch normalization layers improved the validation loss, while for the no-grid model, one batch normalization layer showed similar improvement. As a result, both configurations were incorporated into the optimal CNN model architectures.

### 3.3 Model Fitting

It was decided to fit the optimal grid and no-grid-based CNN models with the full dataset (wheat + grass 2023 and 2024), wheat data (2023 and 2024), and grass data (2023 and 2024). This resulted in a total of six CNN models being fitted and evaluated.

Before fitting the optimal CNN models to the entire dataset, a stability check was performed to assess the model's performance across different datasets. The 10 datasets created during preprocessing (Figure 10) were used to fit the models, allowing for an evaluation of the stability of training and validation metrics, particularly validation loss and epochs. Once the CNN models showed consistent performance and stability across the different input datasets, the model architecture and parameters were finalized and used to fit the full dataset.

#### 3.3.1 10 Dataset Model Fitting



**Figure 12.** Diagram illustrating the steps of the 10-dataset model fitting.

The training metrics retrieved when fitting the models with the different datasets (Figure 12) are shown in Table 9. The fits demonstrate stable performance of the validation loss for both the grid and no-grid CNN models. The number of epochs needed to fit the grid-based models remains stable, while this is less consistent for the no-grid-based model fits. It is expected that, as the dataset size increases, the variation in epochs required for the no-grid-based model fits will decrease.

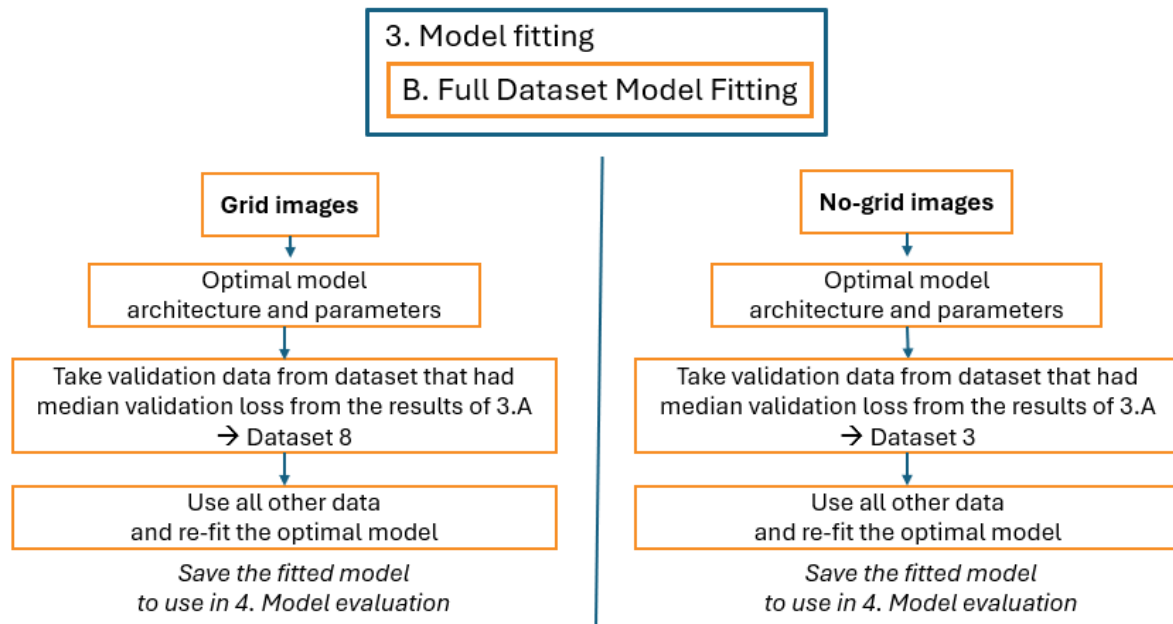
**Table 9.** Training metrics obtained when fitting the optimal grid- and no-grid-based CNN models using 10 different datasets created during preprocessing. The grid-input model architecture consisted of 2 dense layers with 512 and 238 units, dropout rates of 0.5 and 0.2, respectively, and a batch size of 32. The no-grid-input model architecture used 2 dense layers with 512 and 238 units, dropout rates of 0.4 and 0.3, and a batch size of 32.

<i>Grid</i>	<i>Epoc</i>	<i>Val</i>	<i>Train</i>	<i>Val</i>	<i>Train</i>	<i>No-Grid</i>	<i>Epoc</i>	<i>Val</i>	<i>Train</i>	<i>Val</i>	<i>Train</i>
<i>hs</i>	<i>acc</i>	<i>acc</i>	<i>loss</i>	<i>loss</i>		<i>hs</i>	<i>acc</i>	<i>acc</i>	<i>loss</i>	<i>loss</i>	
<b>1</b>	57	0.60	0.62	<b>1.08</b>	0.99	<b>1</b>	105	0.73	0.75	<b>0.76</b>	0.69
<b>*2</b>	53	0.60	0.62	<b>1.08</b>	0.99	<b>2</b>	87	0.73	0.73	<b>0.78</b>	0.74
<b>3</b>	62	0.60	0.63	<b>1.06</b>	0.97	<b>3</b>	68	0.74	0.73	<b>0.76</b>	0.73
<b>4</b>	51	0.60	0.62	<b>1.08</b>	1.00	<b>4</b>	143	0.74	0.77	<b>0.75</b>	0.67
<b>5</b>	69	0.60	0.62	<b>1.08</b>	0.99	<b>5</b>	102	0.73	0.75	<b>0.76</b>	0.71
<b>6</b>	46	0.60	0.62	<b>1.07</b>	1.01	<b>6</b>	151	0.74	0.77	<b>0.77</b>	0.67
<b>7</b>	73	0.60	0.62	<b>1.08</b>	1.00	<b>*7</b>	125	0.73	0.74	<b>0.77</b>	0.72
<b>8</b>	63	0.60	0.62	<b>1.07</b>	0.98	<b>8</b>	62	0.73	0.73	<b>0.79</b>	0.75
<b>9</b>	56	0.60	0.62	<b>1.09</b>	1.00	<b>9</b>	75	0.72	0.75	<b>0.78</b>	0.70
<b>10</b>	58	0.61	0.63	<b>1.08</b>	0.96	<b>10</b>	79	0.73	0.74	<b>0.80</b>	0.72

\* Median performing dataset according to the validation loss.

### 3.3.2 Full Dataset Model Fitting

Given the stability of the CNN models' architecture and hyperparameters, the optimal models were trained on the full dataset (wheat and grass, 2023 and 2024) (Figure 13). This approach utilized all available data—rather than just the training subset—to maximize learning. To mitigate overfitting, model performance was monitored using the validation data from the median-performing dataset (Table 9, based on validation loss), ensuring generalization to unseen data. The resulting CNN models (for both grid and no-grid input images) were then used for evaluation (Section 4). Training metrics from the fitting process are provided in Table 10.



**Figure 13.** Diagram illustrating the steps of the 10-dataset model fitting.

**Table 10.** Training metrics for the Grid and No-grid CNN models, fitted on the full dataset (wheat and grass, 2023–2024) with validation performance monitored using the median-performing subset (see Table 9).

Input type	Epochs	Validation accuracy	Train Accuracy	Validation loss	Train loss
<b>GRID</b>	79	0.62	0.63	1.01	0.97
<b>NO-GRID</b>	112	0.75	0.75	0.71	0.70

### 3.3.3 Wheat/Grass Dataset Model Fitting

The optimal CNN architectures and hyperparameters (identified using the full dataset) were also trained separately on wheat-only and grassland-only data from 2023–2024. Performance metrics for these grass-fitted and wheat-fitted models (both grid and no-grid variants) are provided in **Appendix 2 - Results Grass-fitted Model** and **Appendix 3 - Results Wheat-fitted Model**.

## 3.4 Model Evaluation

The grid and no-grid-based CNN models were evaluated on their performance in predicting the validation polygons (Figure 14) and in predicting each damage in the created damage maps (i.e. full field prediction, Figure 15) (Kjellander et al. 2024). On the full field predictions, a post-analysis has been performed to retrieve statistics on the total area of damage per damage type and damage type ratios.

### 3.4.1 Evaluation Model: Validation Polygons

The evaluation of the validation polygons was done by having the fitted CNN models (grid and no-grid-based wheat, grass, and fulldata-fitted models) classify each of the validation polygons per field and study area (Figure 14). The classification was evaluated using the following metrics:

**Confusion matrix:** A matrix showing the actual damage types on the X-axis and the predicted damage types on the Y-axis. The diagonal shows the amount of correctly predicted validation polygons per damage type.

**Total accuracy:** The total amount of correctly predicted validation polygons divided by the total amount of damages predicted.

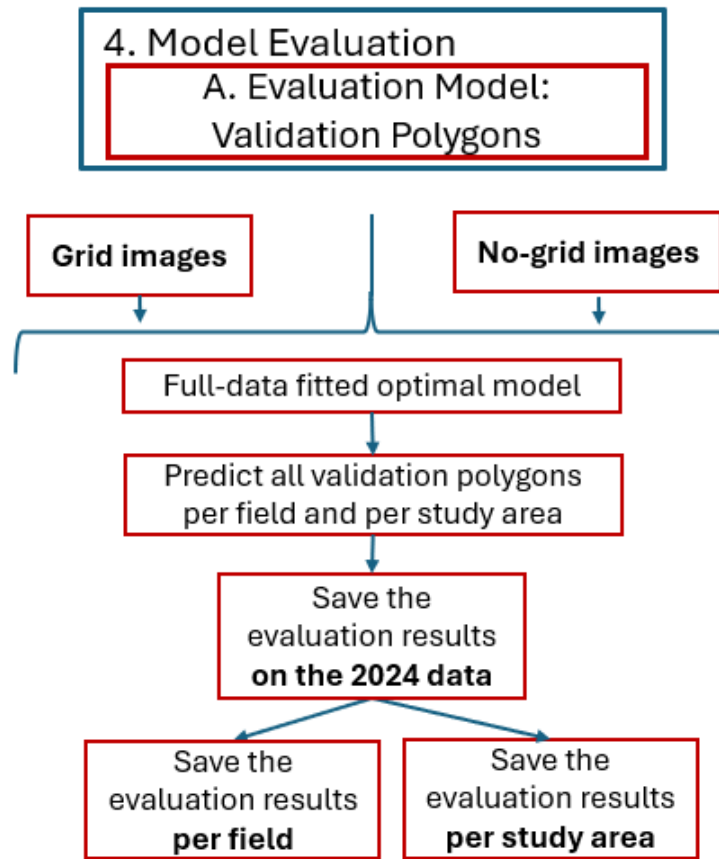
**Total Kappa:** How well the performance of the CNN model was in predicting the validation polygons damage type but accounted for what would be expected by chance.

**Variance metric:** The variance of the *metric* was calculated by taking into account each field that was evaluated in a specific study area.

**Precision per damage type:** The total amount of correctly predicted validation polygons for a specific damage type, divided by the total amount of validation polygons predicted as that specific damage type.

**Recall per damage type:** The total amount of correctly predicted validation polygons for a specific damage type, divided by the total amount of validation polygons that were the specific damage type.

**F1 score per damage type:** The balance between the damage type's precision and recall according to the following formula:  $2 \cdot \frac{Precision * Recall}{Precision + Recall}$



**Figure 14.** Diagram illustrating the steps of the 4. A. Validation Polygon evaluation.

### 3.4.2 Evaluation Model: Full Field Prediction

#### *Full Field Prediction: Creation and Evaluation*

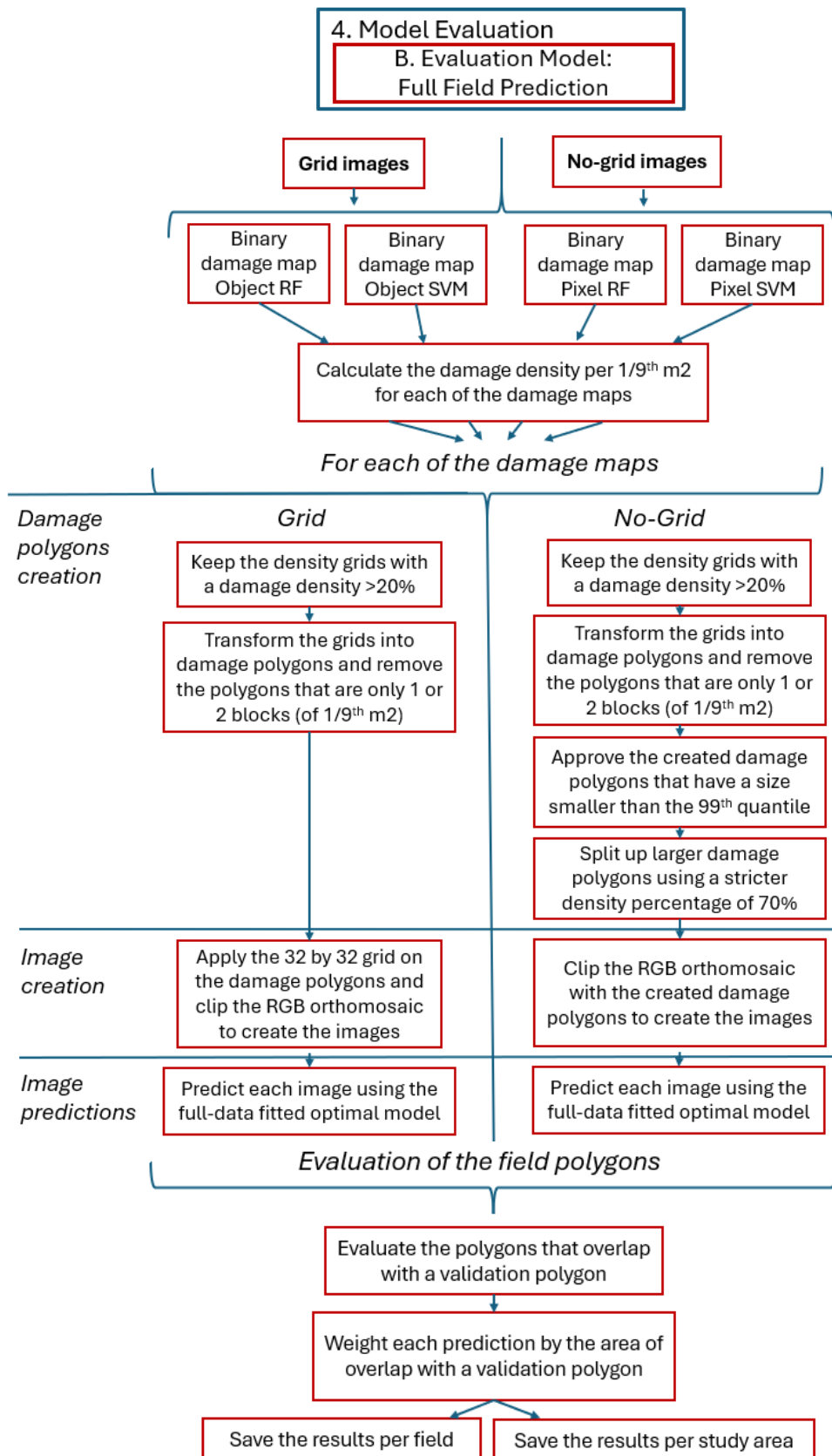
The second evaluation analysed the CNN models' complete predictions across all agricultural fields following the workflow illustrated in Figure 15. The process began by generating damage polygons using binary damage maps from the object- and pixel-based RF/SVM classifications (Kjellander et al. 2024). These maps were first converted to density maps through a  $1/9 \text{ m}^2$  grid ( $4 \times 4$  pixels), then filtered using a 20% density threshold to identify damage areas. Contiguous grid clusters meeting this threshold were converted to damage polygons, while excluding single or double-grid artifacts.

For the no-grid models, additional polygon refinement addressed the challenge of mixed-damage polygons, a key limitation discussed in Section 3.1.1. Each polygon's size was compared against the 99th percentile size of 2023 validation data ( $76.46 \text{ m}^2$ ). Oversized polygons were reprocessed using a stricter 70% density threshold, with the resulting polygons merged with previously accepted ones to create the final set for no-grid image generation.

Image generation differed by model type. Grid-based images were created by applying VGG16-compatible  $32 \times 32$ -pixel grids to the damage polygons and extracting intersecting RGB orthomosaic regions. For no-grid models, the RGB orthomosaic was directly clipped using the refined damage polygons.

The evaluation proceeded by applying all three CNN model variants (full-data, wheat-fitted, and grass-fitted) to the generated images. Validation focused exclusively on areas of overlap between predicted damage polygons and validation polygons, using area-weighted scoring to avoid double-counting detection failures. This approach intentionally excluded unpredicted validation polygon areas from metrics. Results were reported both at the field level and aggregated by study area.





**Figure 15.** Diagram showing the steps of the full field prediction evaluation.

### *Full Field Prediction: Post-Analysis*

A post-analysis was performed on the field-level predictions. The first step involved clipping the predicted damage polygons using the original damage shapes obtained from the initial classification step (Kjellander et al. 2024). Following this, the total area of damage per damage type was calculated and reported in both square meters (m<sup>2</sup>) and hectares (ha). Additionally, two ratios were computed: the proportion of each damage type relative to the total damage area, and the proportion of each damage type relative to the total field area. Lastly, a spatial interpolation was conducted to provide damage statistics for wild boar across each study area in 2024.

## 4 Results

### 4.1 Validation polygons evaluation results

A summary of the validation polygon evaluation results obtained from the grid- and no-grid-based CNN models is provided in Table 10. The models were trained on three different datasets: wheat only, grass only, and the combined (full data) wheat and grass dataset from 2023 and 2024. Table 10 reports key performance metrics, including overall accuracy, Cohen's kappa, and average class-wise precision, recall, and F1 score. Additionally, it highlights the per-class performance for the wild boar damage class as predicted by each model.

Further detailed results for each trained CNN model (i.e., those fitted on grass, wheat, or the full dataset) are presented in the different appendices (Appendix 2-4). These include confusion matrices, per-class performance metrics, and the number of predicted samples. Moreover, the evaluation results are also broken down by study area. For each study area, four separate evaluations are presented: grid-based model on wheatlands, grid-based model on grasslands, no-grid-based model on wheatlands, and no-grid-based model on grasslands.

- **Appendix 2 - Results Grass-fitted Model**  
contains the validation polygons evaluation results of the model fitted on grassland data from 2023 and 2024.
- **Appendix 3 - Results Wheat-fitted Model**  
contains the validation polygons evaluation results of the model fitted on wheat data from 2023 and 2024.
- **Appendix 4 - Results Full-data-fitted Model**  
contains the validation polygons evaluation results of the model fitted on both wheat and grassland data from 2023 and 2024.

**Table 10.** Summary of the evaluation results on the 2024 wheat and grassland validation polygons, using CNN models fitted on grass-only, wheat-only, and full combined datasets.

<b>Wheatlands Total 2024</b>	<i>Overall Average</i>	<i>Overall Kappa</i>	<i>Average Precision</i>	<i>Average Recall</i>	<i>Average F1score</i>
<i>Grid Wheat-fitted Model</i>	0.74	0.61	0.64	0.63	0.62
<i>Grid Fulldata-fitted Model</i>	0.69	0.54	0.57	0.54	0.54
<i>No-Grid Wheat-fitted Model</i>	0.89	0.84	0.78	0.81	0.79
<i>No-Grid Fulldata-fitted Model</i>	0.85	0.79	0.68	0.76	0.71

<b>Wheatlands Total 2024</b>	<i>Wild boar Precision</i>	<i>Wild boar Recall</i>	<i>Wild boar F1 score</i>
<i>Grid Wheat-fitted Model</i>	0.58	0.77	0.66
<i>Grid Fulldata-fitted Model</i>	0.51	0.75	0.61
<i>No-Grid Wheat-fitted Model</i>	0.88	0.90	0.89
<i>No-Grid Fulldata-fitted Model</i>	0.82	0.89	0.85

<b>Grasslands Total 2024</b>	<i>Overall Average</i>	<i>Overall Kappa</i>	<i>Average Precision</i>	<i>Average Recall</i>	<i>Average F1score</i>
<i>Grid Grass-fitted Model</i>	0.77	0.50	0.49	0.69	0.54
<i>Grid Fulldata-fitted Model</i>	0.72	0.47	0.57	0.54	0.55
<i>No-Grid Grass-fitted Model</i>	0.75	0.68	0.81	0.74	0.77
<i>No-Grid Fulldata-fitted Model</i>	0.71	0.62	0.74	0.70	0.69

<b>Grasslands Total 2024</b>	<i>Wild boar Precision</i>	<i>Wild boar Recall</i>	<i>Wild boar F1 score</i>
<i>Grid Grass-fitted Model</i>	0.44	0.59	0.50
<i>Grid Fulldata-fitted Model</i>	0.37	0.49	0.42
<i>No-Grid Grass-fitted Model</i>	0.81	0.55	0.65
<i>No-Grid Fulldata-fitted Model</i>	0.74	0.54	0.63

## 4.2 Field Prediction Evaluations

To improve readability and avoid confusion, this report presents only the full field prediction evaluation for the wheat and grasslands of 2024 in the Jönköping study area, as it provides a comprehensive overview of the overall results obtained from the execution of the CNN models. Table 11 summarizes the overall accuracy, Cohen's kappa, and the average precision, recall, and F1 score based on the best-performing model from the first-step classification. The RF and SVM classification algorithms of the first step classification were trained on 50% of the orthomosaics from each study area, which were treated as separate entities due to their distinct geographical locations (i.e., south–north gradient) and landscape characteristics (i.e., ranging from predominantly agricultural to more forested).

Additionally, two example maps are provided: one of the Jönköping wheatland field *R3002\_141* (Figure 16) and one of the grassland fields *F3496\_27* (Figure 17). These maps illustrate how each CNN model (i.e., those fitted on fulldata and wheat, and fulldata and grass) predicted damage polygons within the respective fields.

For a complete overview of the field prediction evaluations across all four study areas and using all CNN models, we refer to the following appendices: **Appendix 2 - Results Grass-fitted Model**, **Appendix 3 - Results Wheat-fitted Model**, and **Appendix 4 - Results Fulldata-fitted Model**.

**Table 11.** Summary of the full field prediction evaluation results for wheat and grassland in 2024, using CNN models fitted on grass, wheat, and combined (fulldata) datasets. Metrics include overall accuracy, Cohen's kappa, and average precision, recall, and F1 score.

<b>Wheatlands Jönköping 2024</b>	<b>Best Model</b>	<b>Overall Average</b>	<b>Overall Kappa</b>	<b>Average Precision</b>	<b>Average Recall</b>	<b>Average F1score</b>
<i>Grid Wheat-fitted Model</i>	Object RF	0.75	0.56	0.42	0.47	0.44
<i>Grid Fulldata-fitted Model</i>	Object RF	0.68	0.46	0.38	0.43	0.40
<i>No-Grid Wheat-fitted Model</i>	Pixel RF	0.56	0.34	0.34	0.31	0.32
<i>No-Grid Fulldata-fitted Model</i>	Pixel SVM	0.57	0.36	0.36	0.30	0.33

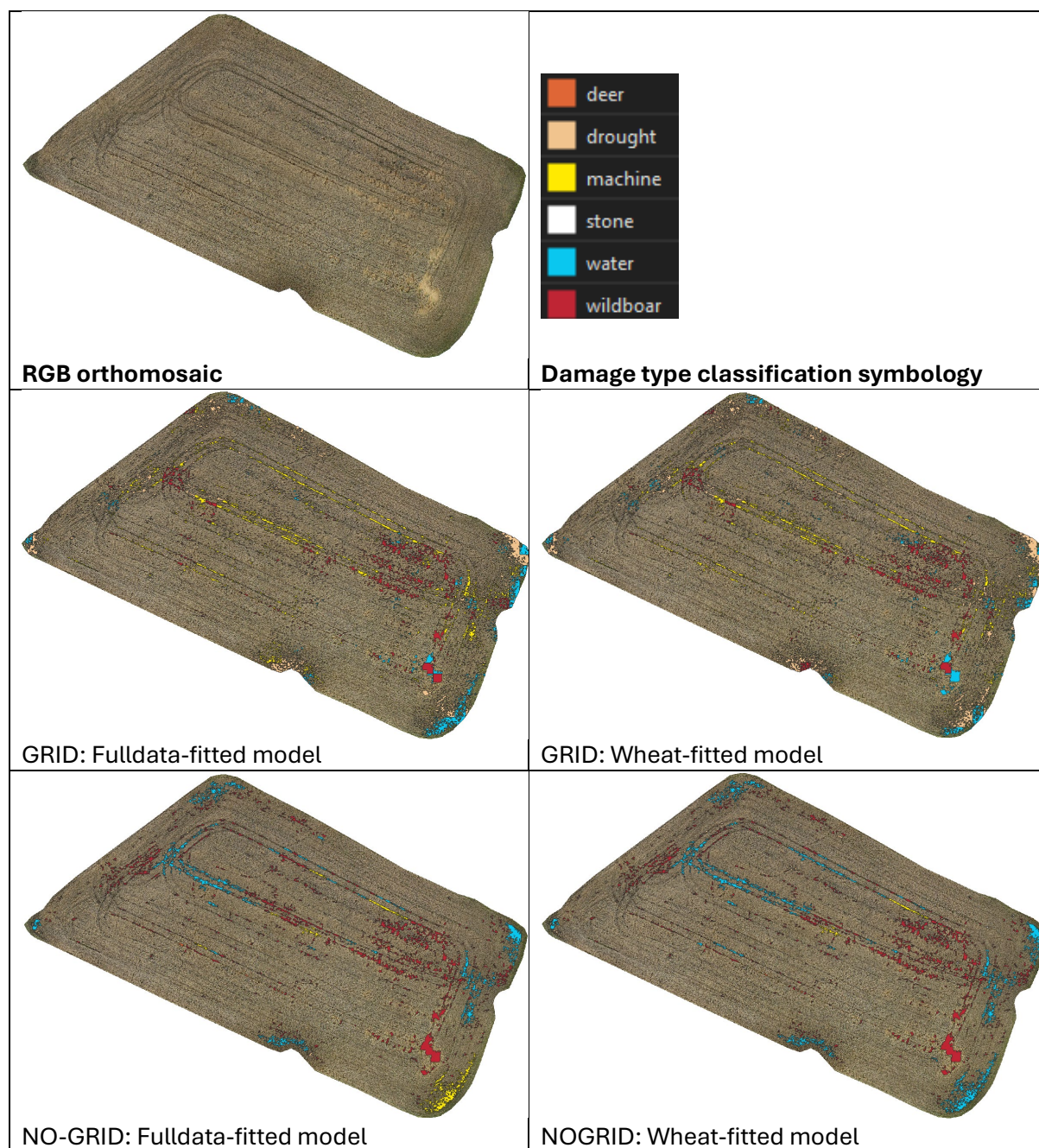
  

<b>Wheatlands Jönköping 2024</b>	<b>Best Model</b>	<b>Wild boar Precision</b>	<b>Wild boar Recall</b>	<b>Wild boar F1 score</b>
<i>Grid Wheat-fitted Model</i>	Object RF	0.63	0.80	0.70
<i>Grid Fulldata-fitted Model</i>	Object RF	0.53	0.78	0.63
<i>No-Grid Wheat-fitted Model</i>	Pixel RF	0.40	0.93	0.56
<i>No-Grid Fulldata-fitted Model</i>	Pixel SVM	0.42	0.90	0.58

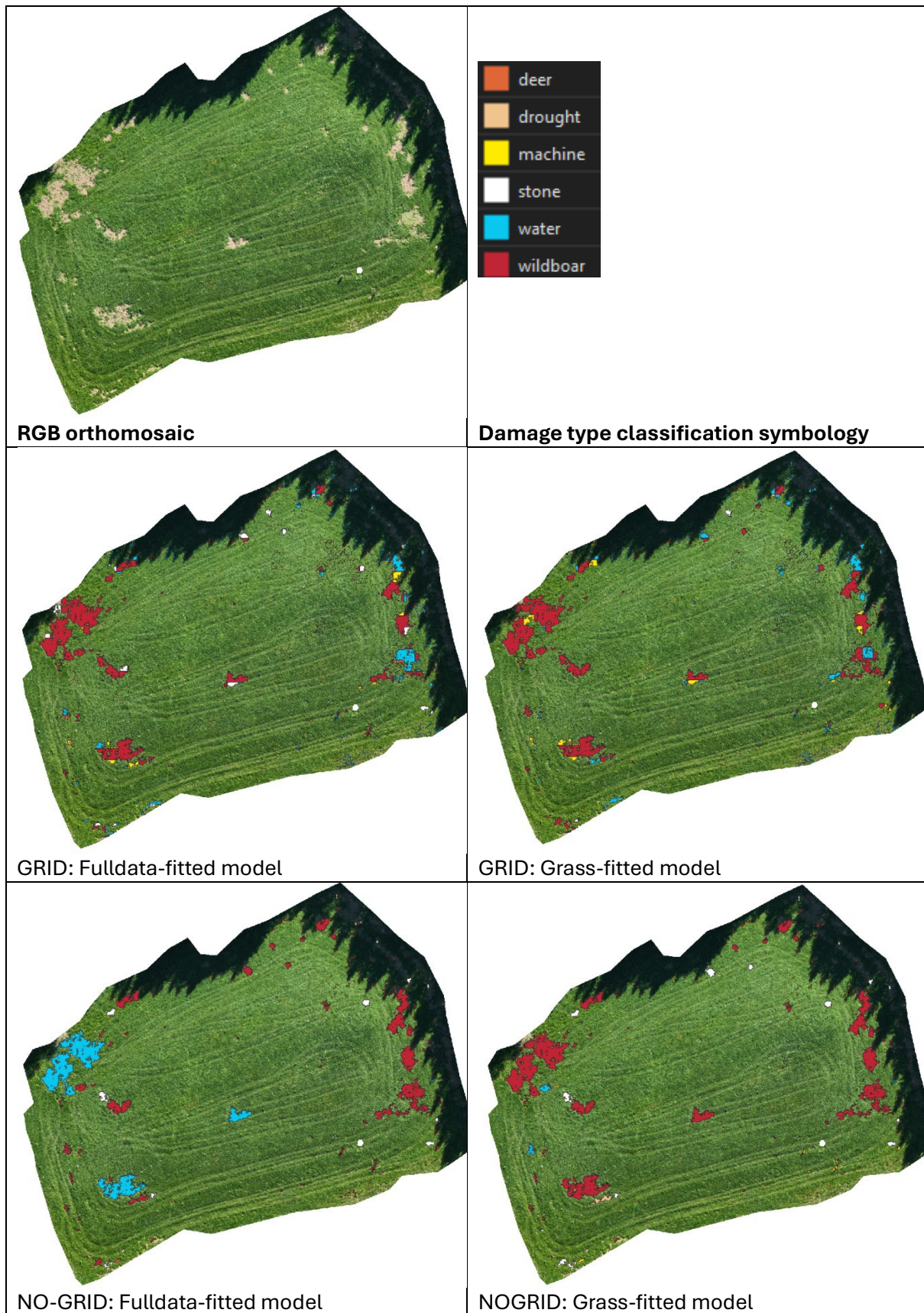
<b>Grasslands Jönköping 2024</b>	<b>Best Model</b>	<b>Overall Average</b>	<b>Overall Kappa</b>	<b>Average Precision</b>	<b>Average Recall</b>	<b>Average F1score</b>
<i>Grid Grass-fitted Model</i>	Pixel-RF	0.63	0.42	0.49	0.44	0.46
<i>Grid Fulldata-fitted Model</i>	Pixel SVM	0.54	0.35	0.39	0.45	0.42
<i>No-Grid Grass-fitted Model</i>	Pixel SVM	0.70	0.54	0.46	0.44	0.45
<i>No-Grid Fulldata-fitted Model</i>	Pixel SVM	0.57	0.34	0.37	0.36	0.36

<b>Grasslands Jönköping 2024</b>	<b>Best Model</b>	<b>Wild boar Precision</b>	<b>Wild boar Recall</b>	<b>Wild boar F1 score</b>
<i>Grid Grass-fitted Model</i>	Pixel-RF	0.38	0.69	0.49
<i>Grid Fulldata-fitted Model</i>	Pixel SVM	0.28	0.57	0.37
<i>No-Grid Grass-fitted Model</i>	Pixel SVM	0.57	0.65	0.60
<i>No-Grid Fulldata-fitted Model</i>	Pixel SVM	0.49	0.67	0.57



**Figure 16.** Wheat Jönköping field called R3002\_141. The RGB orthomosaic, damage type classification symbology and the damage type classifications of the different grid and no-grid-based CNN models fitted on fulldata and wheat data only are presented. The damage polygons are created based on the classification 1 Pixel-based Random Forest model.





**Figure 17.** Grass Jönköping field called F3496\_27. The RGB orthomosaic, damage type classification symbology and the damage type classifications of the different grid and no-grid-based CNN models fitted on fulldata and wheat data only are presented. The damage polygons are created based on the classification 1 Pixel-based Random Forest and Support Vector Machine models.

## 4.3 Post-classification analysis – Damage type ratios

The average damage type ratios for the different fitted models of the wheatlands and grasslands from Jönköping 2024 are summarized in Table 12 and Table 13. For a complete overview of the field prediction evaluations across all four study areas and using all CNN models, please refer to the following appendices: **Appendix 2 - Results Grass-fitted Model**, **Appendix 3 - Results Wheat-fitted Model**, and **Appendix 4 - Results Fulldata-fitted Model**.

### 4.3.1 Wheatlands Jönköping

**Wheatlands Jönköping 2024 average of the object and pixel-based RF and SVM mean Ratio Damage vs Field area: 0.22 (~ 22% on average is classified as damage in the wheat fields of Jönköping by the first step classification (Kjellander et al. 2024))**

**Table 13.** Average ratios of damage type area versus predicted damage area for object- and pixel-based RF and SVM models. The table summarizes the average damage ratios across different damage types within the wheatlands of Jönköping in 2024.

<b>Wheatlands Jönköping 2024</b>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>Grid Wheat-fitted Model</i>	0.24	0.01	0.15	0.27	0.00	0.34
<i>Grid Fulldata-fitted Model</i>	0.25	0.01	0.17	0.27	0.00	0.31
<i>No-Grid Wheat-fitted Model</i>	0.46	0.01	0.07	0.11	0.00	0.36
<i>No-Grid Fulldata-fitted Model</i>	0.26	0.04	0.04	0.14	0.00	0.52

### 4.3.2 Grasslands Jönköping

**Grasslands Jönköping 2024 average of the object and pixel-based RF and SVM mean Ratio Damage vs Field area: 0.17 (~ 17% on average is classified as damage in the wheat fields of Jönköping by the first step classification (Kjellander et al. 2024))**

**Table 14.** Average ratios of damage type area versus predicted damage area for object- and pixel-based RF and SVM models. The table summarizes the average damage ratios across different damage types within the grasslands of Jönköping in 2024.

<b>Grasslands Jönköping 2024</b>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>Grid Grass-fitted Model</i>	0.18	0.01	0.01	0.19	0.03	0.59
<i>Grid Fulldata-fitted Model</i>	0.15	0.03	0.11	0.19	0.07	0.45
<i>No-Grid Grass-fitted Model</i>	0.16	0.04	0.04	0.23	0.02	0.50
<i>No-Grid Fulldata-fitted Model</i>	0.18	0.04	0.03	0.17	0.02	0.57

## 5. Limitations and recommendations

### 5.1 Limitations:

#### 5.1.1 Data:

- The way damage types were classified changed between 2023 and 2024, creating an imbalance in the dataset. This classification system is not fixed and remains open to discussion. For example, the frequent use of the "other" category led to a high number of entries that were impossible to use for training and validating the damage type classification model.
- Parameters for data preprocessing—such as flight settings (40 meters height → 120 meters height), ortho-mosaic creation (spatial resolution 5 → 8 cm), and field selection — were adjusted between the 2023 and 2024 field data collection campaigns. These changes introduced inconsistencies (e.g., data heterogeneity) in the input data.
- Data quality (i.e., UAV images) was influenced by external factors, such as varying weather conditions and heterogeneity among observers.
- Differences in experience, situational awareness, and adaptability among drone operators, field surveyors, and data labelling staff contributed to variations in data collection and labelling.
- Classification tasks were affected by the subjective nature of labelling. Increasing the number of workers involved in labelling, amplified this subjectivity, resulting in greater inconsistency across the dataset.

#### 5.1.2 Model design:

- The current model demands significant computational resources to operate effectively.
- It is semi-automated, meaning that a human operator must validate the results at each step to achieve the final outcome. This design potentially increases processing time and the risk of human-induced errors.
- Robust performance and high accuracy of the model depend on having a large volume of training data, specifically labelled examples.
- The model is written in R, which depends on external packages, introducing certain limitations in processing time, algorithmic flexibility, optimization, generalizing capacity and performance.
- The model relies on convolutional neural network (CNN) layers from the VGG16 model (Simonyan and Zisserman, 2014) and uses data from the ImageNet dataset (Deng et al., 2009) to artificially enhance model's overall performances. More data is needed to increase model's overall performances solely based on internal datasets.
- The model's architecture and parameters are not finalized and may be adjusted based on the characteristics of the input data and the objectives of the analysis.
- So far, only CNN-based deep learning has been implemented, but other computer vision and deep learning models (e.g., Self-supervised learning (SSL), Mask R-CNN, Recurrent Neural Networks (RNNs and LSTMs), etc...) could also be explored.



### 5.1.3 Model validation:

- The validation statistics should be interpreted with caution due to insufficient validation data. They do not accurately reflect real-life scenarios and are based on a dataset that is not sufficiently representative.
- Validation results from 2023 and 2024 are not directly comparable because the 2023 data show a strong bias toward the wild boar damage class, a bias that is less pronounced in the 2024 data.
- The results highlight a significant lack of comprehensive damage representation in the input dataset, which impacts reliability.

## 5.2 Recommendations:

### 5.2.1 Data:

- Clearly define a specific objective to guide both the algorithm design and data collection processes. These two components are closely interdependent and should be developed in alignment with one another.
- Place significant emphasis on harmonizing field data collection, including drone imagery and labelling of pre-processed data. Establish a detailed and standardized protocol prior to any survey to prevent confusion and miscommunication, thereby reducing variability in data quality and quantity.
- Substantially increase the volume of collected field data, including expanding the study areas, fields, and labelled datasets. Achieving better coverage and representativeness among damage classes in the dataset will enhance the model's accuracy and reliability.
- Consider scaling the model to a national level by incorporating airborne data as an alternative to UAV imagery. This approach could improve data uniformity and enable the use of advanced sensors (e.g., LiDAR, hyperspectral imaging, higher-resolution cameras), enhancing input data quality.
- Decide whether to store raw data, which requires substantial storage capacity. Retaining raw data ensures flexibility for future use, allowing it to support alternative objectives or accommodate modifications to the model.

### 5.2.2 Model design:

- Enhance the model's generalization capabilities during its design to broaden its range of potential applications.
- Scaling up the model will require high-performance computing. This can be achieved either by building suitable infrastructure on-site or by partnering with external datacentres. Similarly, data storage solutions can be managed locally or outsourced.
- Further development of the model would benefit from a combination of ecological expertise, particularly in the Swedish agricultural landscape, and advanced software and programming skills.

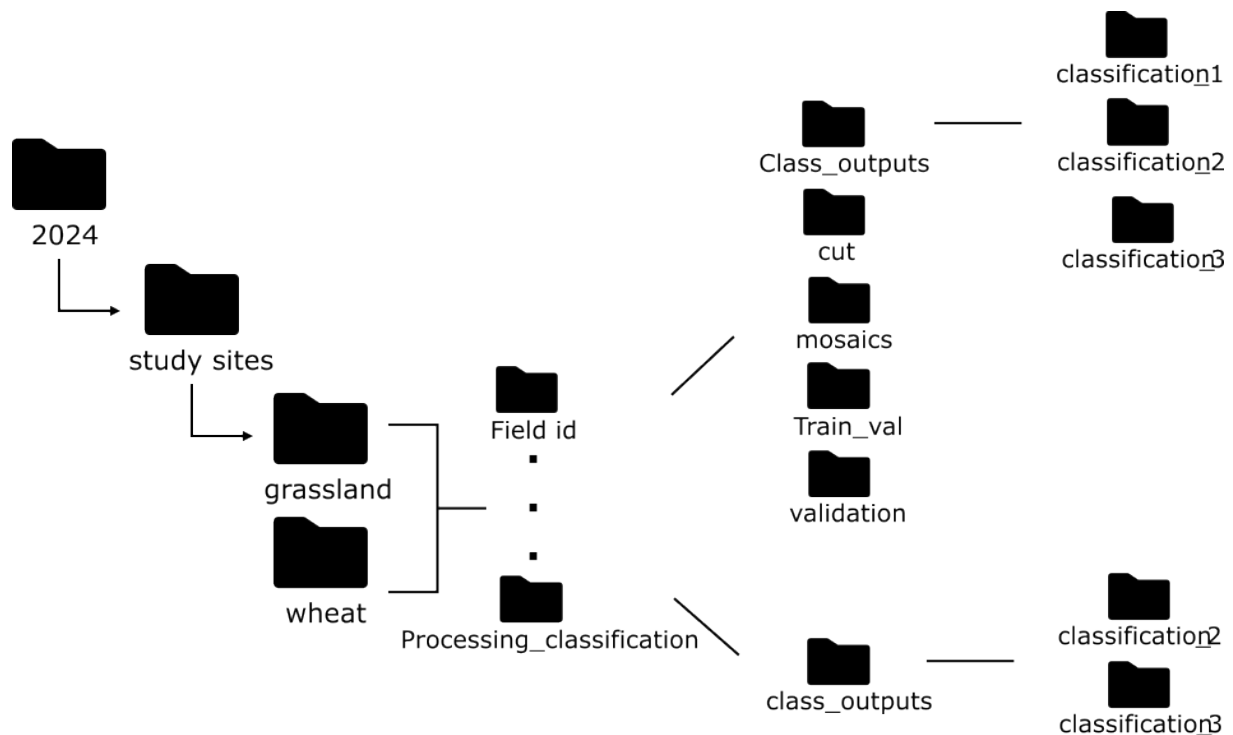
- Additional algorithms (e.g., Self-supervised learning (SSL), Mask R-CNN, Recurrent Neural Networks (RNNs and LSTMs), etc...) should be explored and evaluated to determine their potential to complement, adjust, or replace the current model design.
- Implementing changes and improvements will require an iterative process of testing and refinement. This is time consuming but cannot be avoided to achieve state of the art model design.
- Focus on improving the model's automation to reduce the risk of human errors, model's operation and maintenance costs, as well as model's overall performances and processing time.
- Consider rewriting the model in a programming language that supports hardcoding, such as C++, to enhance performance, processing time, adaptability, and optimization during development and exploitation. This change would provide greater flexibility, modularity and generalizing capacity of the developed model.

## 6. Developed scripts and user guide

### 6.1 The developed scripts and required data folder structure

The implementation of the CNN models was conducted using R version 4.3.2 (2023-10-11) and Python version 3.11. The codebase is organized into two main script groups: one set for the grid-based CNN model and another for the no-grid-based model, as described in Section 3.1.1 Each script corresponds to a step in the overall workflow illustrated in Figure 2, and filenames reflect these step labels for clarity and reproducibility.

To ensure proper execution, the scripts must be run sequentially—for example, script 1A must be completed before running script 1B. In addition, the input data must follow a specific folder structure, shown in Figure 18, which must be in place prior to execution. This organization ensures compatibility between the scripts and the data pipeline, facilitating reproducible and scalable model development across both ecological and computational applications.



**Figure 18.** Required data folder structure for executing the scripts associated with the grid-based and no-grid-based Convolutional Neural Network (CNN) models. This structure must be established prior to running the scripts to ensure correct data access and processing throughout the workflow.

To ensure proper execution of the scripts used for both the grid-based and no-grid-based Convolutional Neural Network (CNN) models, the following data folder structure must be established in advance:

1. cut: This folder must contain a geopackage file named “cut.gpkg”, which includes the field boundaries for each study site.
2. mosaic: This folder should include orthomosaic images in .tif format, specifically the Near-Infrared (NIR), Red Edge, and RGB bands for each field (e.g., fieldname\_re\_mosaic.tif, fieldname\_nir\_mosaic.tif, fieldname\_rgb\_mosaic.tif). Alternatively, a single combined and normalized .tif file containing all bands (e.g., fieldname\_mosaic\_norm.tif) can be used.
3. train\_val: This folder contains the first set of binary damage classifications. Note that these are not used in the CNN-based damage type classification but are relevant for earlier stages of analysis.
4. validation: This folder must include a geopackage file with digitized polygons of field-surveyed damage observations, each labelled with a corresponding damage type (e.g., fieldname\_damage\_polygons.gpkg).
5. class\_outputs: This folder should be created prior to execution (as an empty folder). The scripts will automatically generate three subfolders within it:
  - classification1: Will contain intermediate outputs.
  - classification2: Will include results from the evaluation of the validation polygons (as described in Section 4.1), separated by grid and no-grid model variants, and further

categorized by the training data used: full dataset (grass + wheat), wheat-only, or grass-only.

- classification3: Will store full-field prediction evaluations, again separated into grid and no-grid models and structured by training data type.

6. processing\_classification → class\_outputs: This folder should also be created in advance as an empty directory. The scripts will generate the necessary subfolders:

- classification2: Mirrors the structure and content described above for evaluation of validation polygons (Section 4.1).
- classification3: Contains results from full-field prediction evaluations.

## 6.2 Developed scripts overview and descriptions

Table 15 contains the scripts' names and descriptions for the grid-based and no-grid-based CNN model creations and evaluations. Detailed explanations of the method are in section 3.

**Table 15.** Overview of the scripts available for the grid-based and no-grid-based CNN model creation and evaluation.

GRID	NO-GRID
<p><b>Name:</b> 1A_grid_image_creation_2023data.R</p> <p><b>Description:</b> Creates the grid images using orthomosaics and the validation polygons from 2023 and saves the images of the damages in a specified <i>output folder</i> with the subfolder name 'original_images'. The output folder is created when it does not exist yet, this is also done for the different damage types you want to create images for (each damage type gets its subfolder within the output folder).</p> <p><b>To keep in mind:</b> Define the same <i>output folder</i> for the 2023 and 2024 data if you want to perform the hyperparameter tuning (2) and model fitting (3) with all the data.</p>	<p><b>Name:</b> 1A_nogrid_image_creation_2023data.R</p> <p><b>Description:</b> Creates the no-grid images using orthomosaics and the validation polygons from 2023 and saves the images of the damages in a specified <i>output folder</i> with the subfolder name 'original_images'. The output folder is created when it does not exist yet, this is also done for the different damage types you want to create images for (each damage type gets its subfolder within the output folder).</p> <p><b>To keep in mind:</b> Define the same <i>output folder</i> for the 2023 and 2024 data if you want to perform the hyperparameter tuning (2) and model fitting (3) with all the data.</p>

<p><b>Name:</b> 1A_grid_image_creation_2024data.R</p> <p><b>Description:</b> Creates the grid images using the orthomosaics and the validation polygons from 2024 and saves the images of the damages in a specified <i>output folder</i> with the subfolder name 'original_images'. The output folder is created when it does not exist yet, this is also done for the different damage types you want to create images for (each damage type gets its subfolder within the output folder).</p> <p><b>To keep in mind:</b> Define the same <i>output folder</i> for the 2023 and 2024 data if you want to perform the hyperparameter tuning (2) and model fitting (3) with all the data.</p>	<p><b>Name:</b> 1A_nogrid_image_creation_2024data.R</p> <p><b>Description:</b> Creates the no-grid images using the orthomosaics and the validation polygons from 2024 and saves the images of the damages in a specified <i>output folder</i> with the subfolder name 'original_images'. The output folder is created when it does not exist yet, this is also done for the different damage types you want to create images for (each damage type gets its subfolder within the output folder).</p> <p><b>To keep in mind:</b> Define the same <i>output folder</i> for the 2023 and 2024 data if you want to perform the hyperparameter tuning (2) and model fitting (3) with all the data.</p>
<p><b>Name:</b> 1B_grid_image_preperation.R</p> <p><b>Description:</b> Define the <i>output folder</i> that contains all the created images. This script prepares the images to be used for the hyperparameter tuning Component 2. The preparation consists of ensuring that all the images have the same width, height, and #channels. Next to this, if wanted, it can be indicated how many augmentations (currently up to 5) per damage type are performed. All data is randomly split up in 50% Train and validation, and 50% test. The created dataset is saved in the same folder containing the images in a subfolder named: hyp_dataset. This folder is automatically created should it not exist yet.</p> <p><b>To keep in mind:</b> The data is split up so that each damage type is represented as equally as possible (with a maximum of 5 augmentations) in the train, validation, and test data.</p>	<p><b>Name:</b> 1B_nogrid_image_preperation.R</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>
<p><b>Name:</b> 1C_10dataset_creation.R</p> <p><b>Description:</b> This script creates 10 different datasets by randomly splitting the prepared CNN images.</p>	<p><b>Name:</b> 1C_10dataset_creation</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>

<p>These datasets are saved in the <i>output folder</i> with a subfolder called: 10datasets. This subfolder is automatically created when it is not yet present in the images folder.</p>	
<p><b>Name:</b> 2A_hyperparameter_tuning.R</p> <p><b>Description:</b> The script runs the hyperparameter tuning on the data saved in the subfolder hyp_dataset. A new folder within the <i>output folder</i> is automatically created called hyp_results when this folder is not present. In this folder, the fitting history in the form of a CSV file is saved for each hyperparameter tuning combination.</p> <p><b>To keep in mind:</b> The architecture is set to two dense layers for which the search grid can be filled in. From the 5-channel data, 3 channels are extracted which is RGB at the moment, this can be changed.</p>	<p><b>Name:</b> 2A_hyperparameter_tuning.R</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>
<p><b>Name:</b> 2B_finetuning_batchnormalization.R</p> <p><b>Description:</b> This script fine-tunes the found hyperparameters using batch normalization once or twice. The output is saved in the hyp_outputs subfolder.</p>	<p><b>Name:</b> 2B_finetuning_batchnormalization.R</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>
<p><b>Name:</b> 3A_10dataset_modelfitting.R</p> <p><b>Description:</b> The script fits the best-found model from component 2 with each of the 10 datasets created in 1C. A new subfolder will be automatically created (if not present yet) called 10datasets_modelfit within the <i>output folder</i>. This subfolder will contain the created model fits per dataset and the training history per dataset. Next to this will there be a CSV file created with all the results from the datasets summarized together.</p>	<p><b>Name:</b> 3A_10dataset_modelfitting.R</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>
<p><b>Name:</b> 3B_fulldataset_modelfitting.R</p> <p><b>Description:</b> This script fits the best-found model architecture and parameters from</p>	<p><b>Name:</b> 3B_fulldataset_modelfitting.R</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>

<p>component 2 with all the data (fulldata, wheat, or grass; train and test) and uses the validation dataset of the median-performing dataset from step 3A for validation during the training. The fitted model will be saved with the name <code>bestmodel_fulldataset.h5</code> as well as the training history file called <code>bestmodel_fulldataset.csv</code>. The results are saved in the <i>output folder</i> in a subfolder called <code>fulldataset/wheat/grass_modelfit</code>, this subfolder is created automatically when it does not exist yet.</p>	
<p><b>Name:</b> 4A_fulldata_evaluation_validation_polygons</p> <p><b>Description:</b> This script evaluates the performance of a specified model (i.e. <code>fulldata_fitted</code>, <code>wheat_fitted</code> or <code>grass_fitted</code>) fitted in the previous step 3B. And reports each field's result in their subfolder called <code>class_outputs/classification2/grid/fulldata_fitted_modelORwheat_fitted_model</code> and for each study area in <code>processing_classification/classification2/grid/fulldata_fitted_model</code></p>	<p><b>Name:</b> 4A_fulldata_evaluation_validation_polygons</p> <p><b>Description:</b> This script evaluates the performance of the <code>fulldata_fitted</code> model fitted in the previous step 3B. And reports each field result in their subfolder <code>class_outputs/classification2/nogrid/fulldata_fitted_model</code> and for each study area in <code>processing_classification/classification2/nogrid/fulldata_fitted_model</code></p>
<p><b>Name:</b> 4Bi_grid_damage_polygon_creation_2024</p> <p><b>Description</b> This script creates damage polygons in a grid format for each of the fields in a specified study area and crop of the 2024 data. The script only works if a field has the cut file present and the outputs from classification 1 are available. The classification 1 output should be in the <code>class_outputs</code> subfolder of a field. The damage polygons created for each of the classification 1 <code>objectRF</code>, <code>objectSVM</code>, <code>pixelRF</code> and <code>pixelSVM</code> models will be saved in the <code>field_name/class_outputs/classification3/grid/classification_method_damage_polygons.gpkg</code></p>	<p><b>Name:</b> 4Bi_nogrid_damage_polygon_creation_2024</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p> <p>Damage polygons saved in the <code>field_name/class_outputs/classification3/grid/classification_method_damage_polygons.gpkg</code></p>
<p><b>Name:</b> 4Bii_grid_fullfield_prediction_2024</p> <p><b>Description</b> This script predicts the damage polygons created in the previous script. The model to be used for the prediction needs to be</p>	<p><b>Name:</b> 4Bii_gnoid_fullfield_prediction_2024</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p>

<p>specified (fulldata, wheat, or grass). The results will be saved in <i>field_name/class_outputs/classification3/grid/fulldataORwheatORgrass_model_outputs/classification_method_grid_type_prediction.gpkg</i></p>	<p>The results are saved in <i>field_name/class_outputs/classification3/grid/fulldataORwheatORgrass_model_outputs/classification_method_nogrid_type_prediction.gpkg</i></p>
<p><b>Name:</b> 4Biii_grid_fullfield_prediction_evaluation_2024</p> <p><b>Description:</b> These scripts evaluates the field predictions that have validation polygons present for each field separately and for the entire study area. The results are saved for each field in: <i>Field_name/class_outputs/classification3/grid/fulldataORwheatORgrass_model_results/field_evaluation.csv</i>. The study area results are saved in <i>study_area/crop/processing_classification/classification3/grid/FulldataORwheatORgrass_model_results/crop_confusion_matrices</i></p>	<p><b>Name:</b> 4Biii_nogrid_fullfield_prediction_evaluation_2024</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p> <p>The results are saved for each field: <i>Field_name/class_outputs/classification3/nogrid/fulldataORwheatORgrass_model_results/field_evaluation.csv</i>. The study area results are saved in: <i>study_area/crop/processing_classification/classification3/nogrid/FulldataORwheatORgrass_model_results/crop_confusion_matrices</i></p>
<p><b>Name:</b> 4Biv_grid_post_analysis_original_ratios</p> <p><b>Description:</b> Performs the post analysis containing reporting the ratios of damage per damage type compared to the total damage and total field area. The results also contain information on the amount of damage that is removed from the original damage maps of classification 1. The result is in subfolder: <i>Study_area/crop/processing_classification/classification3/grid/fulldataORwheatORgrass_model_results/classification_method_study_area_crop_post_analysis_area_ratios.csv</i></p> <p>These scripts will also clip the predicted damage polygons.gpkg to the original shapes of the damages obtained from the output of classification 1. This clipped prediction is saved in: <i>Field_name/class_outputs/classification3/grid/fulldataORwheatORgrass_model_results/classification_methpd_grid_type_prediction_clipped.gpkg</i>.</p>	<p><b>Name:</b> 4Biv_nogrid_post_analysis_original_ratios</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p> <p>The result is in subfolder: <i>Study_area/crop/processing_classification/classification3/nogrid/fulldataORwheatORgrass_model_results/classification_method_study_area_crop_post_analysis_area_ratios.csv</i></p> <p>The clipped predictions are in subfolder: <i>Field_name/class_outputs/classification3/nogrid/fulldataORwheatORgrass_model_results/classification_methpd_nogrid_type_prediction_clipped.gpkg</i>.</p>



<p><b>Name:</b> 4Bv_grid_damage_type_areas</p> <p><b>Description:</b> This script attaches to the cut.gpkg the total damage area and total damage areas per class (in m2 and ha) together with the ratios between the total damage area and the field area. This result is saved in: <i>Field_name/class_outputs/classification3/grid/fulldataORwheatORgrass_model_results/classification_method_classified_damage_type_area.gpkg</i></p>	<p><b>Name:</b> 4Bv_nogrid_damage_type_areas</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p> <p>The results are in subfolder for each field: <i>Field_name/class_outputs/classification3/nogrid/fulldataORwheatORgrass_model_results/classification_method_classified_damage_type_area.gpkg</i></p>
<p><b>Name:</b> 4Bvi_grid_damage_spatial_stats</p> <p><b>Description:</b> This script merges the output of the previous script into one geopackage for each study area. This is saved in: <i>Study_area/crop/processing_classification/grid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_damage_type_all_stats.gpkg</i></p> <p>Next to this is the wild boar damage area overlayed with a 1 x 1 km grid in which it is transformed into a raster where the damaged area is summer. This raster is saved in: <i>Study_area/crop/processing_classification/grid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_wb_damage_all.tif</i></p> <p>Lastly, the raster is used to perform an interpolation. The smoothed interpolation result in saved in: <i>Study_area/crop/processing_classification/grid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_wb_damage_all_interpolated.tif</i></p>	<p><b>Name:</b> 4Bvi_nogrid_damage_spatial_stats</p> <p><b>← THIS SCRIPT IS THE SAME AS USED FOR THE GRID ANALYSIS</b></p> <p>Results in: <i>Study_area/crop/processing_classification/nogrid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_damage_type_all_stats.gpkg</i></p> <p><i>Study_area/crop/processing_classification/nogrid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_wb_damage_all.tif</i></p> <p><i>Study_area/crop/processing_classification/nogrid/fulldataORwheatORgrass_model_outputs/study_area_crop_classification_method_wb_damage_all_interpolated.tif</i></p>

## 6.3 Estimated running times of the developed scripts

The processing times per script are based on the available computational resources (i.e., **PC Unit:** HP Z4 TWR Base unit G5 775W RCTO // **CPU:** Intel Xeon W5-2465X, 4.50GHz, 33.75MB cache,16 Cores 200W // **GPU:** NVIDIA RTX A4500 20GB GDDR6 4x DisplayPort // **Memory:**

4x32GB DDR5 4800 DIMM ECC REG (1CPU configuration) // **Storage:** HP Z Turbo 2TB PCIe-4x4 2280 TLC M.2 SSD // **OS:** Windows 11 Pro 64-bit) as well as the type, size, and number of datasets processed. Detailed information on each script's running time per study area can be found in Section: 7. *Extra, Running times*.

## 1. Preprocessing:

**1. A. Image creation: 24 hours for the grid** image creation of the data from 2023 and 2024 on the grass and wheatlands taking only **6 classes** (i.e. deer, drought, machine, stone, water, wild boar) into account. **30 hours for all 12 classes** (i.e. badger, deer, drought, machine, stone, water, wild boar, wildlife trails, wells, lay, and other) into account.

**1. A. Image creation: 1.5 hours for the no-grid** image creation of the data from 2023 and 2024 on the grass and wheatlands taking only **6 classes** (i.e. deer, drought, machine, stone, water, wild boar) into account. **1.5 hours for all 12 classes** (i.e. badger, deer, drought, machine, stone, water, wild boar, wildlife trails, wells, lay, and other) into account.

**1. B. Image Preparation: 3.5 hours for the grid** image preparation of the images created from 2023 and 2024 for the **6 classes** (i.e. deer, drought, machine, stone, water, wild boar).

**1. B. Image Preparation: 10 minutes for the no-grid** image preparation of the images created from 2023 and 2024 for the **6 classes** (i.e. deer, drought, machine, stone, water, wild boar).

**1. C. 10 Dataset Creation: 1.5h for the grid** prepared images.

**1. C. 10 Dataset Creation: 0.5h for the no-grid** prepared images.

## 2. Hyperparameter tuning:

**Grid:** Depending on the amount of combinations to try. Given you want to try about 81 combinations. And 2 more model fittings for the fine-tuning.

Each model takes about: 1.6h (per combination) \* 83 = 133h = **5.5 days**

**No\_Grid:** Depending on the amount of combinations to try. Given you want to try about 81 combinations.

Each model takes about: 1.4h (per combination) \* 83 = 116h = **4.8 days**

## 3. Model fitting:

**3. A. 10 dataset model fitting: 16h** for the grid.

**3. A. 10 dataset model fitting: 14h** for the no-grid.

**3. B. Full dataset model fitting: 4h** for the grid.

**3. B. Full dataset model fitting: 3.75h** for the no-grid.

## 4. Model Evaluation:

**4. A. Fulldata evaluation validation polygons: 0.5h** for the grid.

**4. A. Fulldata evaluation validation polygons: 5 min** for the no-grid.

**4. B. Full field prediction evaluation: 89 hours** for the grid to create the damage polygons for the fields of wheat and grasslands in Jönköping and predicting and evaluating it with one CNN model.

**4. B. Full field prediction evaluation: 40 hours** for the no-grid to create the damage polygons for the fields of wheat and grasslands in Jönköping and predicting and evaluating it with one CNN model.

## Total Creation Time

Total time grid to create and evaluate one CNN model (fulldata or wheat or grass fitted) with these six damage type classes (i.e. deer, drought, machine, stone, water, wild boar): **272 hours = 11.3 days**

Total time no-grid to create and evaluate one CNN model (fulldata or wheat or grass fitted) with these six damage type classes (i.e. deer, drought, machine, stone, water, wild boar): **176 hours = 7.3 days**

## Total User Time

Total user time grid: When a CNN model is created, fitted and evaluated (i.e. ready to be used) then the total time to predict the damages in the agricultural wheat and grasslands of Jönköping would be (given the current data and CNN model): 65 hours = **2.7 days**

Total user time no-grid: When a CNN model is created, fitted and evaluated (i.e. ready to be used) then the total time to predict the damages in the agricultural wheat and grasslands of Jönköping would be (given the current data and CNN model): 35 hours = **1.5 days**

## 7. Extra, Running times:

Script Grid	Duration			
1A_grid_image_creation_2024data (Times for wheat image creation, 6 classes)	Blekinge: 3849s (1h)	Jönköping: 2845s (0.75h)	Örebro: 8147s (2.25h)	Södermanland: 1792s (0.5h)
1A_grid_image_creation_2024data (Times for wheat image creation, all classes)	Blekinge: 9532s (2.5h)	Jönköping: 4898s (1.5h)	Örebro: 10888s (3h)	Södermanland: 1661s (0.5h)
1B_nogrid_image_preparation.R	2023 & 2024, Grass + Wheat			12416s (3.5h)
1B_nogrid_image_preparation.R Wheat data 2023/2024 only	2023 & 2024, Wheat			4635s (1.25h)

1C_10dataset_creation.R	2023 & 2024, Grass + Wheat			4883s (1.5h)
3A_10dataset_modelfitting.R	2023 & 2024, Grass + Wheat			57672s (16h)
3B_fulldataset_modelfitting.R	2023 & 2024, Grass + Wheat			13795s (4h)
3B_fulldataset_modelfitting.R <i>Wheat data 2023/2024 only</i>	2023 & 2024, Wheat			7473s (2h)
4A_fulldata_evaluation_validation_polygons	2023 & 2024, Grass + Wheat			1203 (0.5h)
4A_fulldata_evaluation_validation_Polygons <i>Wheat data 2024 only</i>	2024 wheat			1342s (0.5h)
4Bi_grid_damage_polygon_creation_2024	Blekinge	Örebro	Jönköping Wheat: 169500s 47 hours	Södermanland
4Bi_grid_damage_polygon_creation_2024			Jönköping Grass: 23309 (6.5h)	
4Bii_grid_fullfield_prediction_2024 Using Fulldata-fitted model	Blekinge	Örebro	Jönköping Wheat: 34372s (9.5h)	Södermanland
4Bii_grid_fullfield_prediction_2024 Using wheat-fitted model	Blekinge	Örebro	Jönköping Wheat: 34633 (9.6h)	Södermanland
4Bii_grid_fullfield_prediction_2024 Using fulldata-fitted model	Blekinge	Örebro	Jönköping grass: 8210s (2.3h)	Södermanland
4Bii_grid_fullfield_prediction_2024 Using grass-fitted model	Blekinge	Örebro	Jönköping grass: 8089s (2.2h)	Södermanland
4Biii_grid_fullfield_prediction_evaluation_2024 Using Fulldata-fitted model	Blekinge	Örebro	Jönköping Wheat: 11348s (3.2h)	Södermanland
4Biii_grid_fullfield_prediction_evaluation_2024 Using Wheat-fitted model	Blekinge	Örebro	Jönköping Wheat: 11425s (3.2h)	Södermanland

4Biii_ grid_fullfield_prediction_ evaluation_2024 Using Fulldata-fitted model	Blekinge	Örebro	Jönköping Grass: 6972s	Södermanland
4Biii_ grid_fullfield_prediction_ evaluation_2024 Using grass-fitted model	Blekinge	Örebro	Jönköping Grass: 6858s (1.9h)	Södermanland
4Biv_grid_post_analysis_o riginal_ratio Using fulldata-fitted model			Jönköping grass: 4061s (1.1h)	
4Biv_grid_post_analysis_o riginal_ratio Using grass-fitted model			Jönköping grass: 4045s (1.1h)	
4Biv_grid_post_analysis_o riginal_ratio Using fulldata-fitted model			Jönköping wheat: 45117s (12.5h)	
4Biv_grid_post_analysis_o riginal_ratio Using wheat-fitted model			Jönköping wheat: 41555s (11.5h)	
4Bv_grid_damage_type_ar eas Using grass-fitted model			Jönköping grass: 25s	
4Bv_grid_damage_type_ar eas Using fulldata-fitted model			Jönköping grass: 28s	
4Bv_grid_damage_type_ar eas Using fulldata-fitted model			Jönköping wheat: 29s	
4Bv_grid_damage_type_ar eas Using wheat-fitted model			Jönköping wheat: 30s	
<i>Extra:</i> Increasing_data_analysis	2023 + 2024 Grass + Wheat 10% – 20% – 30% – 40% – 50% – 60% – 70%- 80% – 90%- 100%			68633s (19h)
<i>Extra:</i> Increasing_data_analysis	2023 + 2024 Wheat 10% – 20% – 30% – 40% – 50% – 60% – 70%- 80% – 90%- 100%			76635s (21.3h)
<i>Extra:</i> Increasing_data_analysis	2023 + 2024 Grass 10% – 20% – 30% – 40% – 50% – 60% – 70%- 80% – 90%- 100%			37584s (10.4h)

Script No-Grid	Duration			
1A_nogrid_image_creation_2024data (Wheat image creation of 2024)	Blekinge: 166s (0h)	Örebro: 340s (0h)	Jönköping: 548s (0h)	Södermanland: 101s (0h)
1B_nogrid_image_preperation.R	2023 & 2024, Grass + Wheat			544s (10min)
1B_nogrid_image_preperation.R Wheat data 2023/2024 only	2023 & 2024, Wheat			250s (5min)
1C_10dataset_creation.R	2023 & 2024 Grass + Wheat			1700s (0.5h)
3A_10dataset_modelfitting.R	2023 & 2024 Grass + Wheat			50805s (14h)
3B_fulldataset_modelfitting.R	2023 & 2024 Grass + Wheat			13505s (3.75h)
3B_fulldataset_modelfitting.R Wheat data 2023/2024 only	2023 & 2024, Wheat			6231s (1.75h)
4A_fulldata_evaluation_validation_polygons	2024, Grass + Wheat			211s (0h)
4Bi_nogrid_damage_polygon_creation_2024	Blekinge Grass: 753s (10min)	Örebro Grass: 3359s (1h)	Jönköping Grass: 2336s (40min)	Södermanland Grass: 3444s (1h)
4Bi_nogrid_damage_polygon_creation_2024	Blekinge	Örebro	Jönköping Wheat: 19838s (5.5h)	Södermanland
4Bii_nogrid_fullfield_prediction_2024 Using Fulldata-fitted model	Blekinge	Örebro	Jönköping Wheat: 47711 (13.3h)	Södermanland
4Bii_nogrid_fullfield_prediction_2024 Using wheat-fitted model	Blekinge	Örebro	Jönköping Wheat: 48594 (13.5h)	Södermanland
4Bii_nogrid_fullfield_prediction_2024 Using Fulldata-fitted model	Blekinge Grass: 1913s	Örebro Grass: 7415s	Jönköping Grass: 9429s	Södermanland Grass: 9548s (2.7h)
4Bii_nogrid_fullfield_prediction_2024 Using grass-fitted model	Blekinge Grass: 1916s	Örebro Grass: 7318s	Jönköping Grass: 9319s	Södermanland Grass: 9797s
4Biii_nogrid_fullfield_prediction_evaluation_2024 Using Fulldata-fitting model	Blekinge Grass: 474s	Örebro Grass: 2097s (35min)	Jönköping Grass: 2067s (34min)	Södermanland Grass: 3340s
4Biii_nogrid_fullfield_prediction_evaluation_2024 Using Fulldata-fitted model	Blekinge	Örebro	Jönköping Wheat: 5302s (1.5h)	Södermanland
4Biii_nogrid_fullfield_prediction_evaluation_2024 Using wheat-fitted model	Blekinge	Örebro	Jönköping Wheat: 5608s (1.6h)	Södermanland

4Biii_nogrid_fullfield_prediction_evaluation_2024 Using Grass-fitted model	Blekinge	Örebro	Jönköping Wheat: 2394s (40min)	Södermanland
4Biv_grid_post_analysis_original_ratio Fulldata-fitted model			Jönköping grass: 3456s (58min)	
4Biv_grid_post_analysis_original_ratio grass-fitted model			Jönköping grass: 3437 (57min)	
4Biv_grid_post_analysis_original_ratio Fulldata-fitted model			Jönköping wheat: 56420s (15.7h)	
4Biv_grid_post_analysis_original_ratio wheat-fitted model			Jönköping wheat: 55800s (15.5h)	
4Bv_nogrid_damage_type_areas Using grass-fitted model			Jönköping grass: 27s	
4Bv_nogrid_damage_type_areas Using fulldata-fitted model			Jönköping grass: 26s	
4Bv_nogrid_damage_type_areas Using fulldata-fitted model			Jönköping wheat: 26s	
4Bv_nogrid_damage_type_areas Using wheat-fitted model			Jönköping wheat: 29s	

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# Appendix 1: *Increasing Data Accuracy Prospect*

The following results were calculated using the 2023 and 2024 grass and wheat data to fit the grid- and no-grid-based fulldata, wheat, and grass CNN models with an increasing amount of data, providing a prospect on the expected amount of data needed to reach a certain accuracy.

## Contents

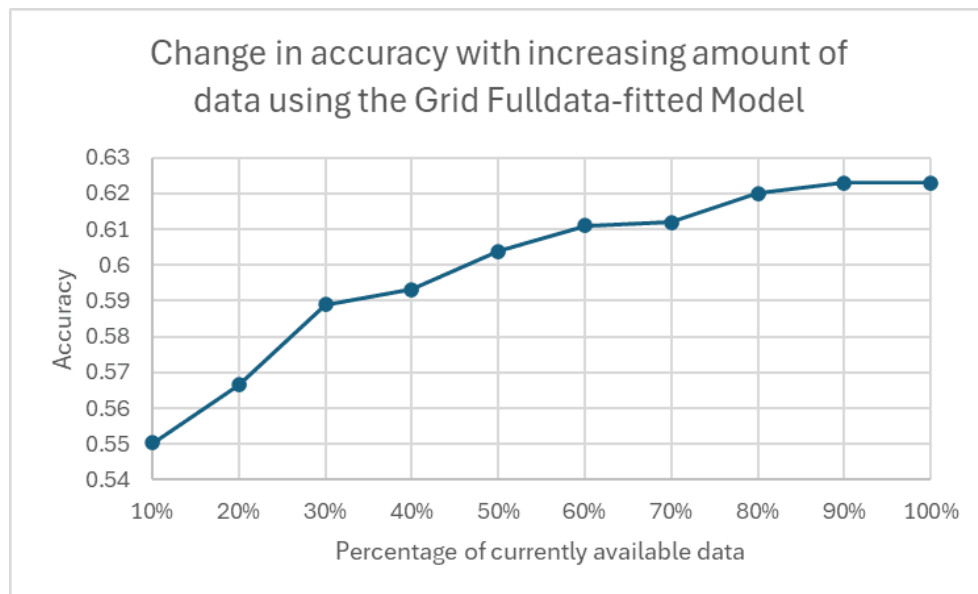
<b>1. Fulldata-fitted model – Increasing Data Prospect.....</b>	<b>58</b>
1.1 Grid: Fulldata-fitted Model	58
1.1.1 Grid: Fulldata-fitted Model – Overall accuracy .....	58
1.1.2 Grid: Fulldata-fitted Model – Wild boar accuracies.....	59
1.2. No-Grid: Fulldata-fitted Model	59
1.2.1 No-Grid: Fulldata-fitted Model – Overall accuracies.....	59
1.1.2 No-Grid: Fulldata-fitted Model – Wild boar accuracies .....	60
<b>2. Wheat-fitted model – Increasing Data Prospect .....</b>	<b>61</b>
2.1 Grid: Wheat-fitted Model	61
2.1.1 Grid: Wheat-fitted Model – Overall accuracy.....	61
2.1.2 Grid: Wheat-fitted Model – Wild boar accuracy .....	62
2.2 No-Grid: Wheat-fitted Model	62
2.2.1 No-Grid: Wheat-fitted Model – Overall accuracy .....	62
2.2.2 No-Grid: Wheat-fitted Model – Wild boar accuracy .....	63
<b>3. Grass-fitted model – Increasing Data Prospect .....</b>	<b>64</b>
3.1 Grid: Grass-fitted Model	64
3.1.1 Grid: Grass-fitted Model – Overall accuracy.....	64
3.1.2 Grid: Grass-fitted Model – Wild boar accuracy .....	65
3.2 No-Grid: Grass-fitted Model	65
3.2.1 No-Grid: Grass-fitted Model – Overall accuracy .....	65
3.2.2 No-Grid: Grass-fitted Model – Wild boar accuracy .....	66

# 1. Fulldata-fitted model – Increasing Data Prospect

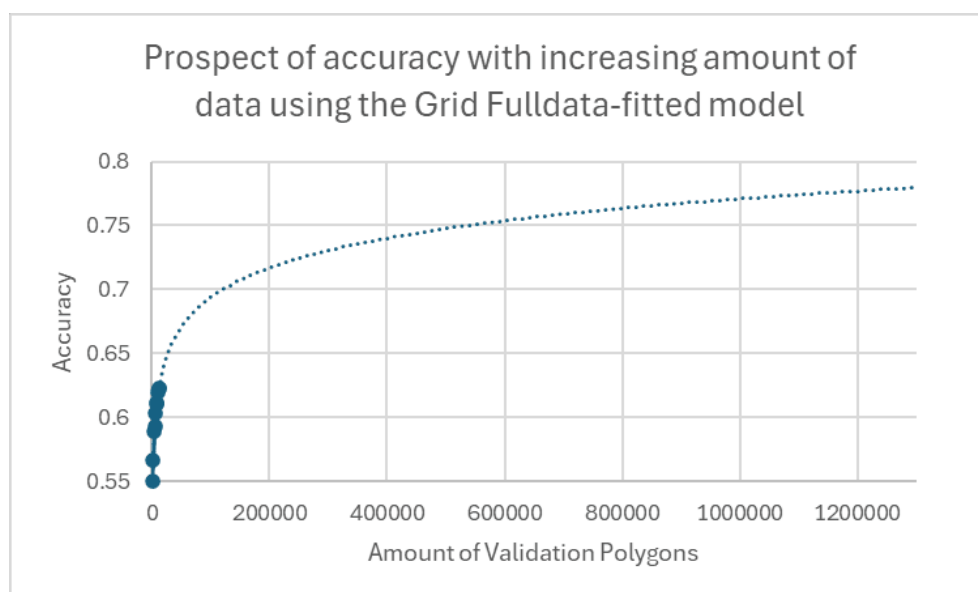
## 1.1 Grid: Fulldata-fitted Model

### 1.1.1 Grid: Fulldata-fitted Model – Overall accuracy

By fitting a logarithmic model, the prospect is that 100 times more wheat+grass data (1.299.100 validation polygons) than what is currently available as data (12.991 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach about 78% accuracy (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the Grid Fulldata-fitted Model.

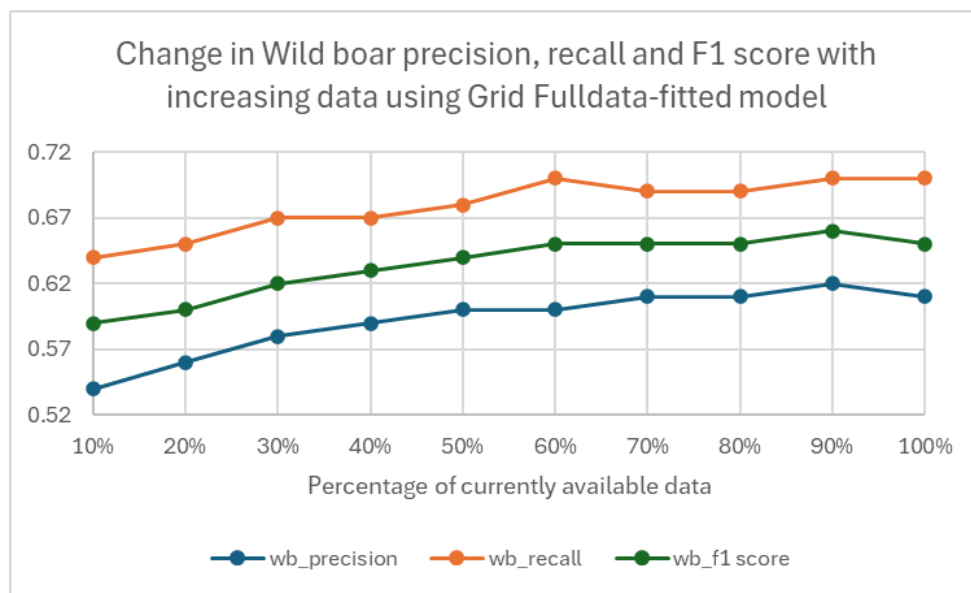


**Figure 3.** Change in accuracy with an increasing amount of data using the Grid Fulldata-fitted Model.



**Figure 4.** The prospect of accuracy with increasing data using the Grid Fulldata-fitted Model. Up to 100x more data than currently available.

### 1.1.2 Grid: Fulldata-fitted Model – Wild boar accuracies



## 1.2. No-Grid: Fulldata-fitted Model

### 1.2.1 No-Grid: Fulldata-fitted Model – Overall accuracies

By fitting a logarithmic model, the prospect is that **100 times** more wheat+grass data (1.299.100 validation polygons in total) than what is currently available (12.991 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach **about 90% accuracy** (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the No-Grid Fulldata-fitted Model.

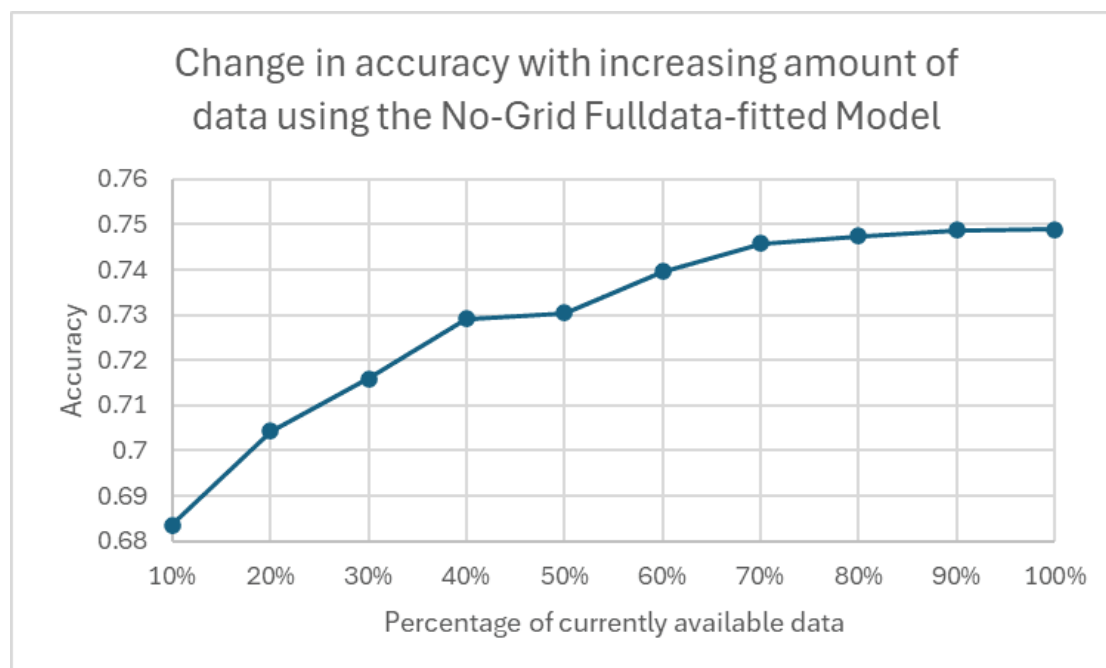
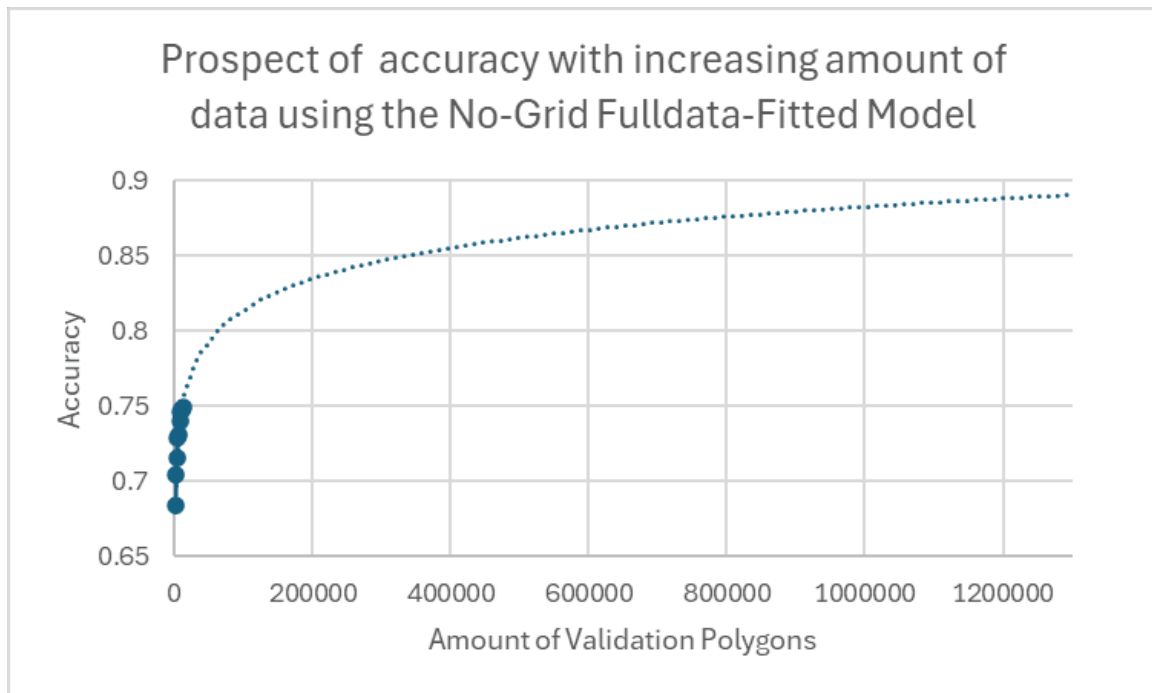
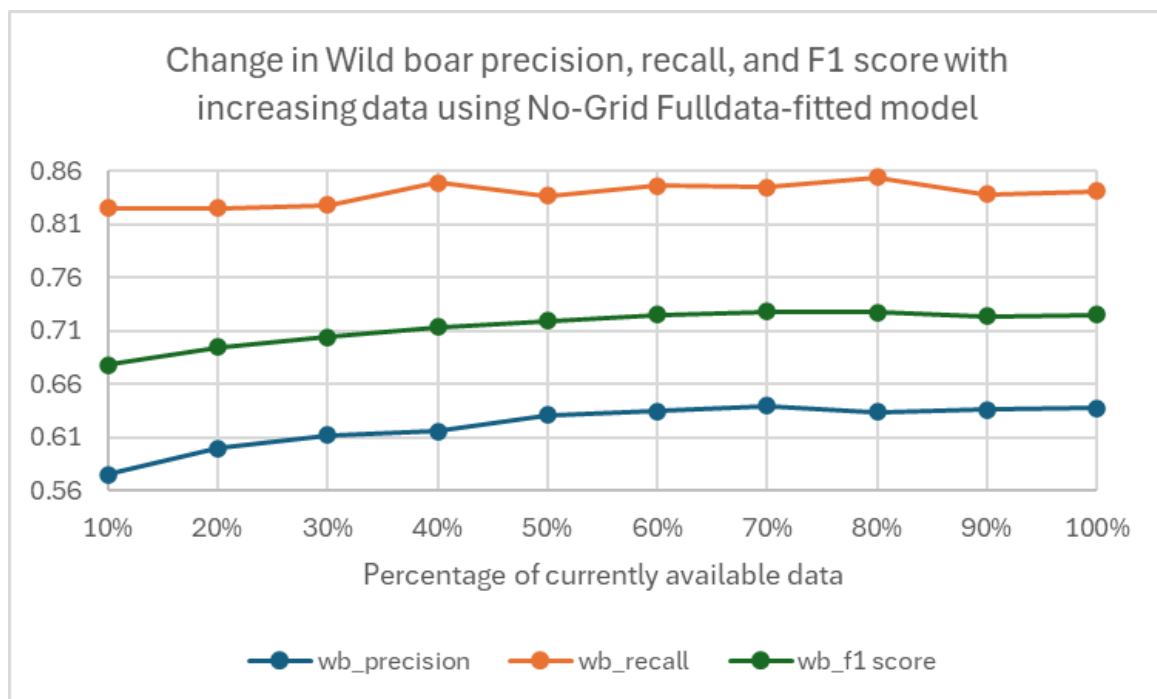


Figure 5. Change in accuracy with increasing amount of data using the NO-Grid Fulldata-fitted Model.



**Figure 6.** The prospect of accuracy with increasing data using the No-Grid Fulldata-fitted Model. Up to 100x more data than currently available.

### 1.1.2 No-Grid: Fulldata-fitted Model – Wild boar accuracies

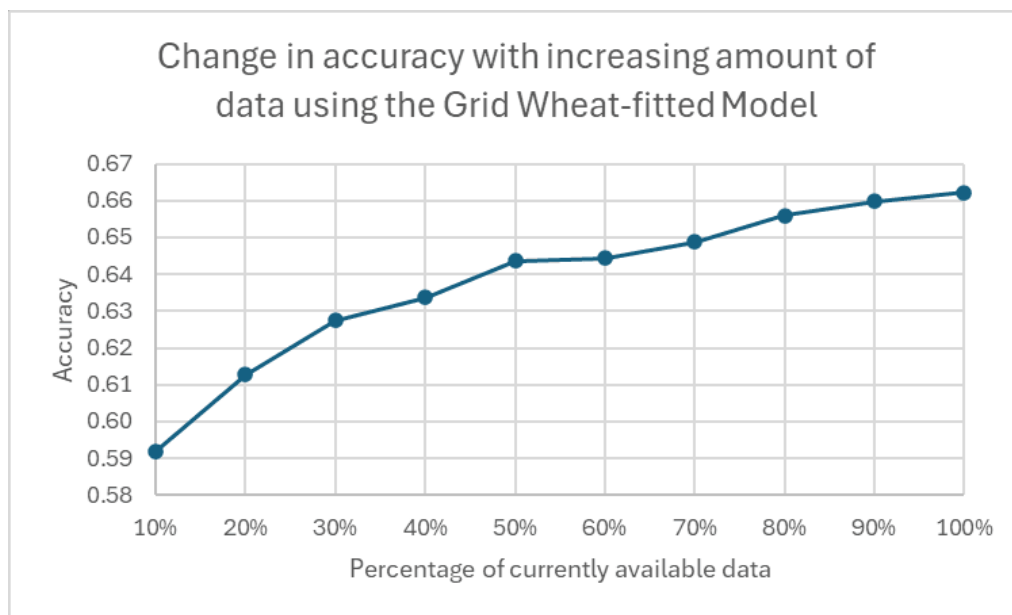


## 2. Wheat-fitted model – Increasing Data Prospect

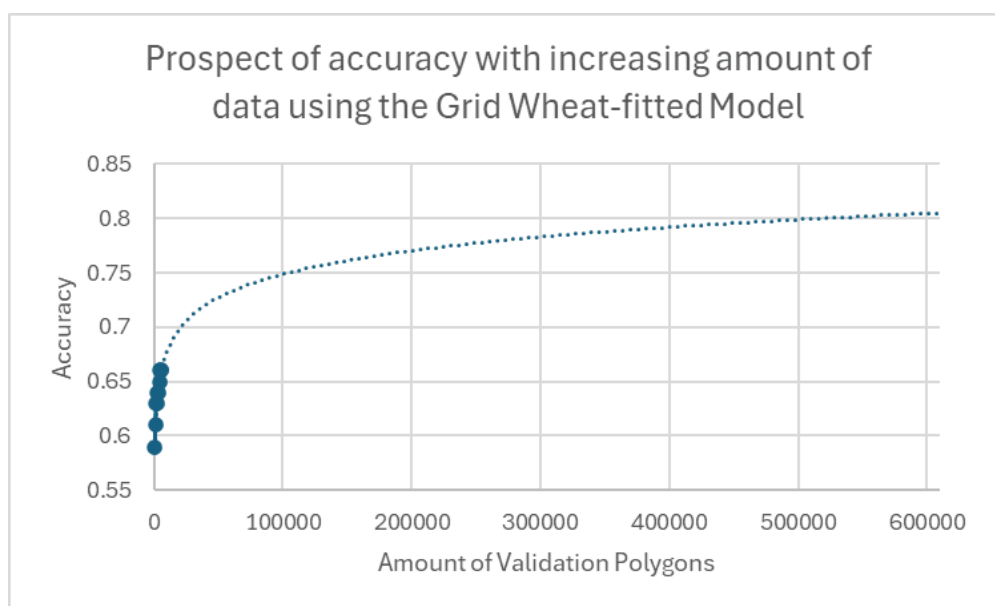
### 2.1 Grid: Wheat-fitted Model

#### 2.1.1 Grid: Wheat-fitted Model – Overall accuracy

By fitting a logarithmic model, the prospect is that **100 times** more wheat data (609.700 validation polygons in total) than what is currently available (6097 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach **about 80% accuracy** (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the Grid Wheat-fitted Model.

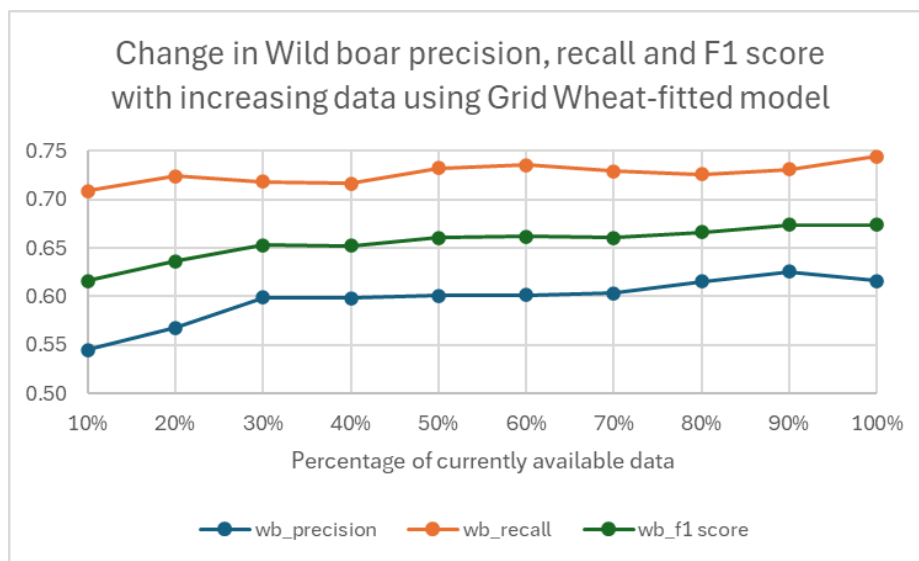


**Figure 7.** Change in accuracy with an increasing amount of data using the Grid Wheat-fitted Model.



**Figure 8.** The prospect of accuracy with increasing data using the Grid Wheat-fitted Model. Up to 100x more data than currently available.

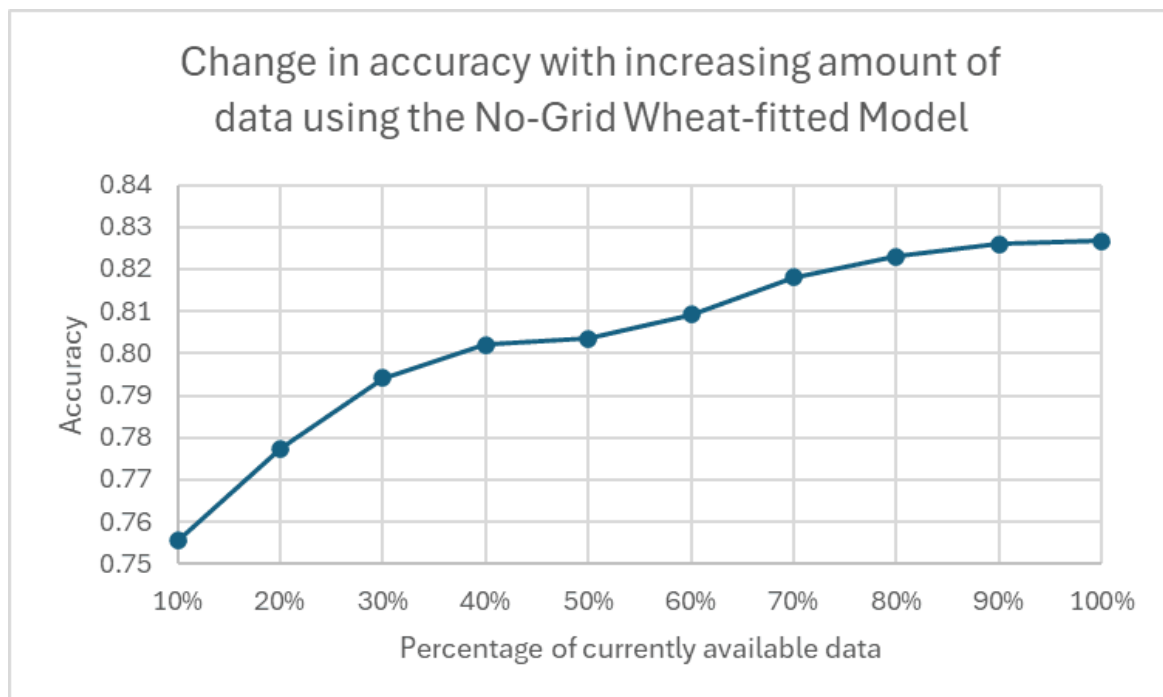
### 2.1.2 Grid: Wheat-fitted Model – Wild boar accuracy



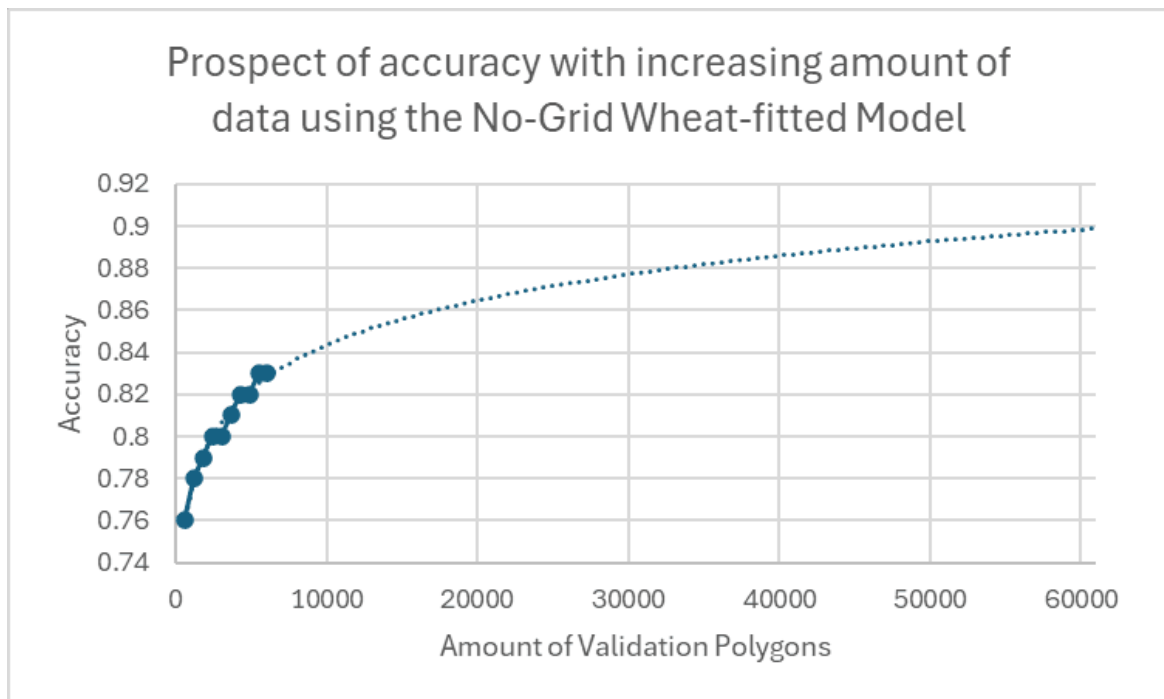
## 2.2 No-Grid: Wheat-fitted Model

### 2.2.1 No-Grid: Wheat-fitted Model – Overall accuracy

By fitting a logarithmic model, the prospect is that **10 times** more wheat data (60970 validation polygons) than what is currently available (6097 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach **90% accuracy** (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the No-Grid Wheat-fitted Model.

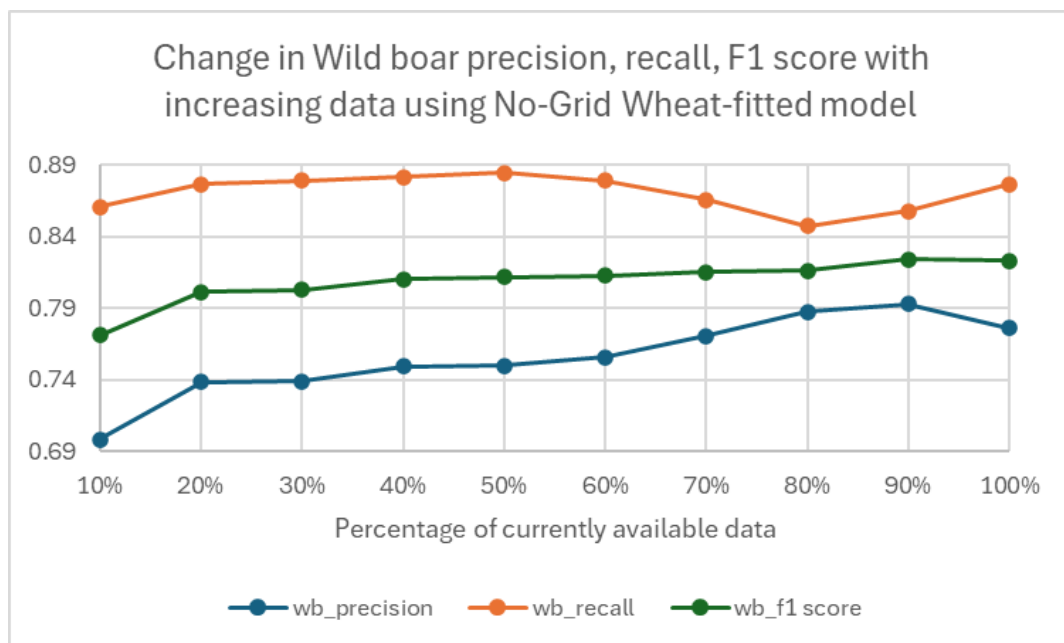


**Figure 9.** Change in accuracy with an increasing amount of data using the No-Grid Wheat-fitted Model.



**Figure 10.** The prospect of accuracy with increasing data using the No-Grid Wheat-fitted Model. Up to 10x more data than currently available.

### 2.2.2 No-Grid: Wheat-fitted Model – Wild boar accuracy

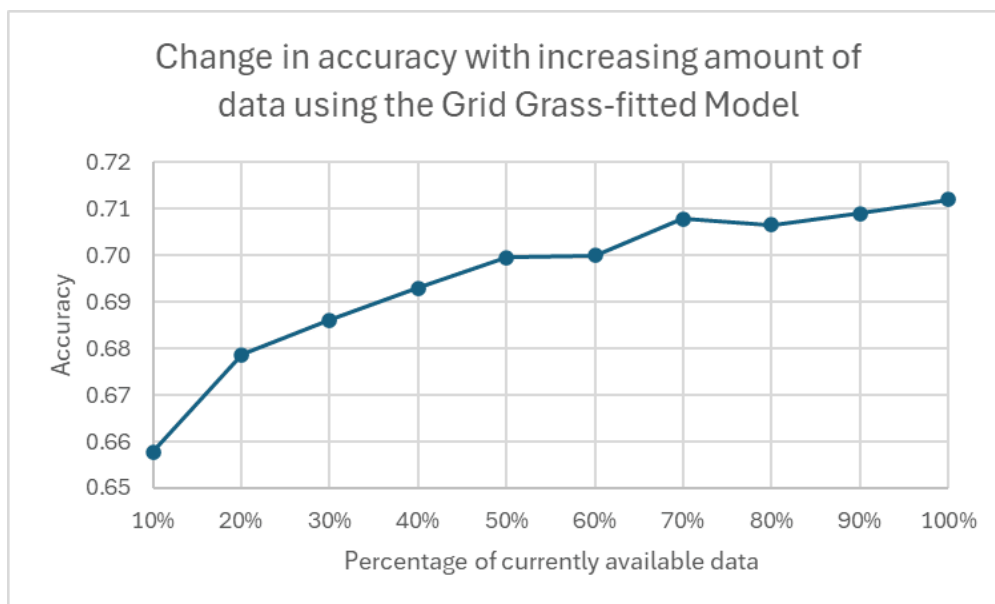


### 3. Grass-fitted model – Increasing Data Prospect

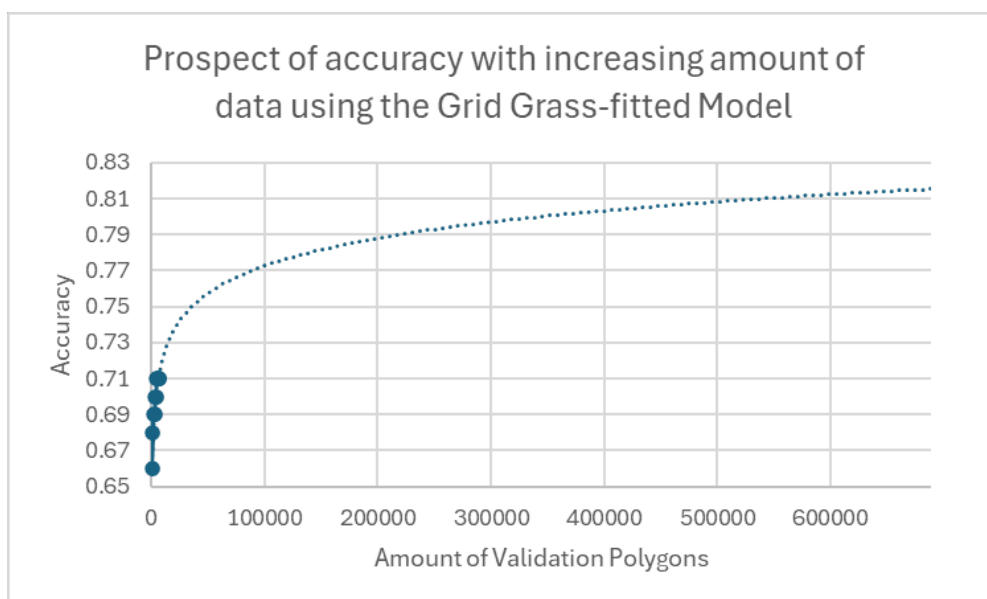
#### 3.1 Grid: Grass-fitted Model

##### 3.1.1 Grid: Grass-fitted Model – Overall accuracy

By fitting a logarithmic model, the prospect is that **100 times** more grass data (689.400 validation polygons) than what is currently available (6894 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach **above 80% accuracy** (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the Grid Grass-fitted Model.



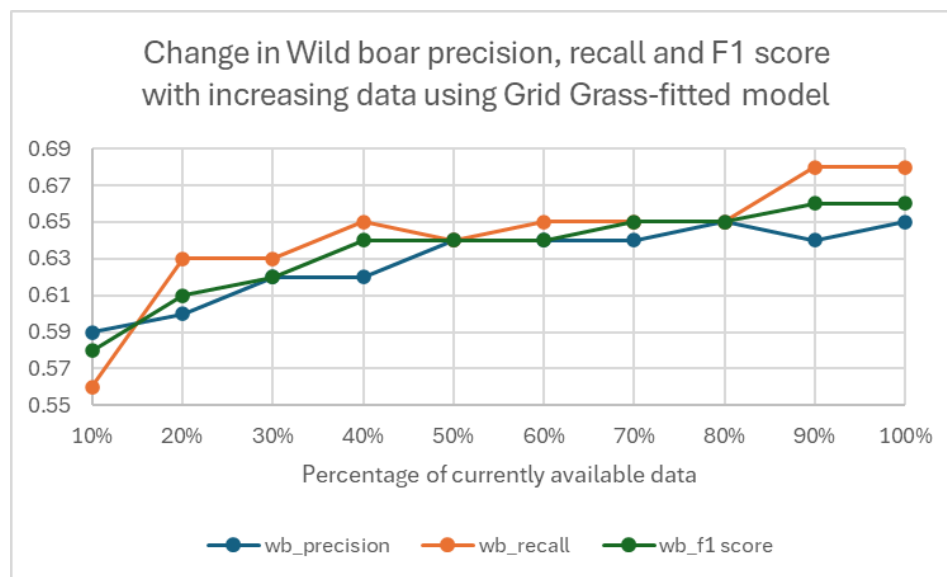
**Figure 11.** Change in accuracy with an increasing amount of data using the Grid Grass-fitted Model.



**Figure 12.** The prospect of accuracy with increasing data using the No-Grid Grass-fitted Model. Up to 100x more data than currently available.



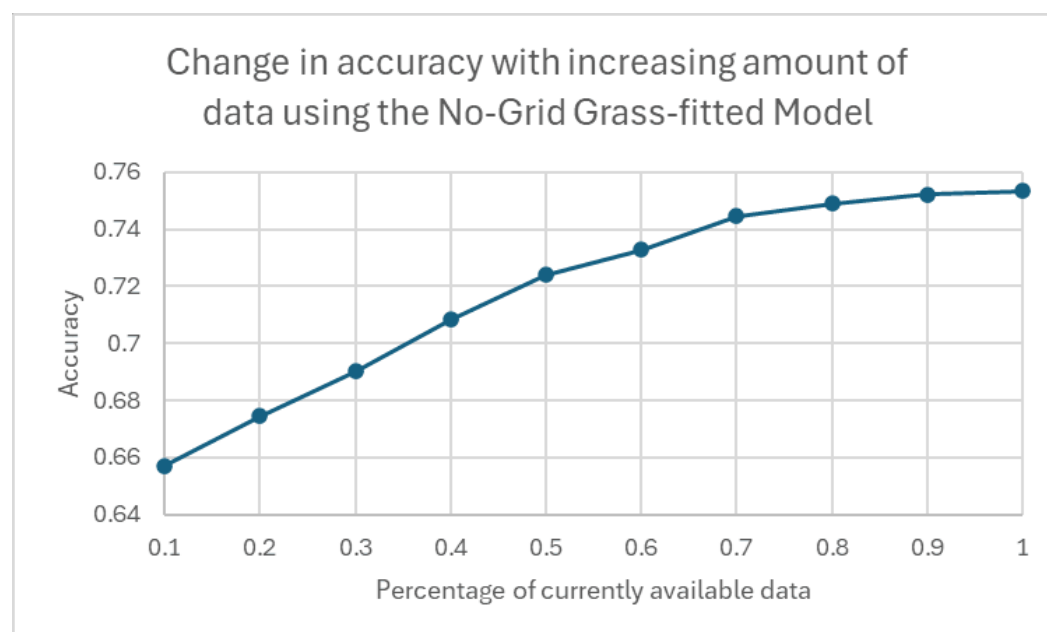
### 3.1.2 Grid: Grass-fitted Model – Wild boar accuracy



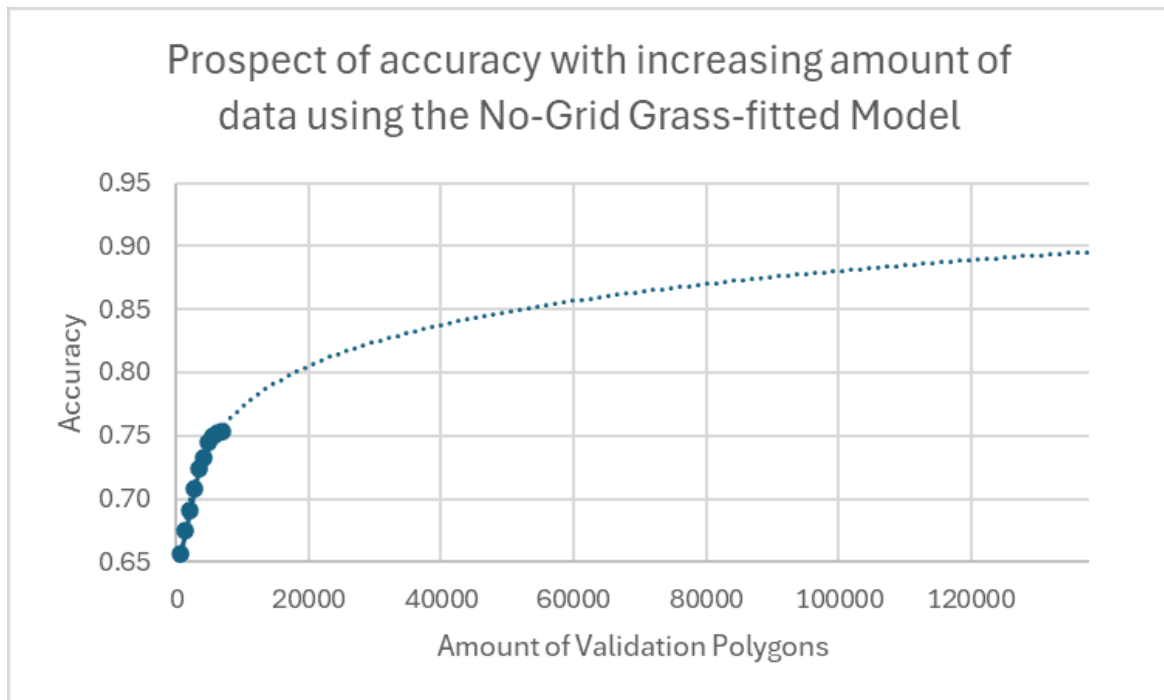
## 3.2 No-Grid: Grass-fitted Model

### 3.2.1 No-Grid: Grass-fitted Model – Overall accuracy

By fitting a logarithmic model, the prospect is that **20 times** more grass data (137.880 validation polygons) than what is currently available (6894 validation polygons for the classes deer, drought, machine, stone, water, and wild boar) is required to reach **90% accuracy** (based on this data and using the current CNN model architecture and parameters, fitted on the 6 classes: deer, drought, machine, stone, water, and wild boar) using the No-Grid Grass-fitted Model.

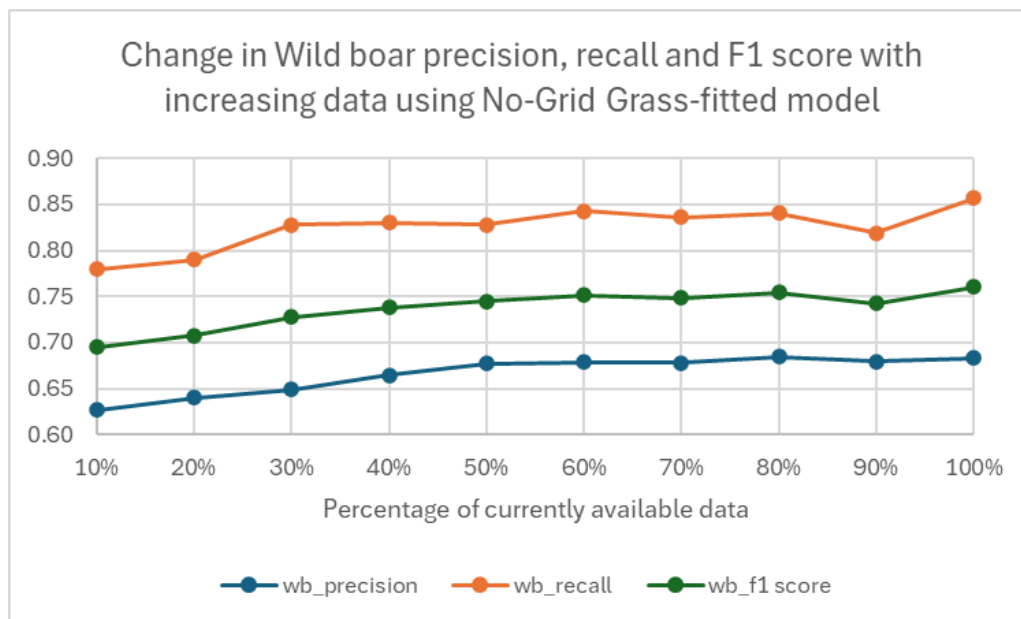


**Figure 13.** Change in accuracy with an increasing amount of data using the No-Grid Grass-fitted Model.



**Figure 14.** The prospect of accuracy with increasing data using the No-Grid Grass-fitted Model. Up to 20x more data than currently available.

### 3.2.2 No-Grid: Grass-fitted Model – Wild boar accuracy



# Appendix 2: Results - Grass-fitted Model

The following results were calculated using the 2023 grass and 2024 grass data to fit the grid- and no-grid-based CNN models.

## Contents

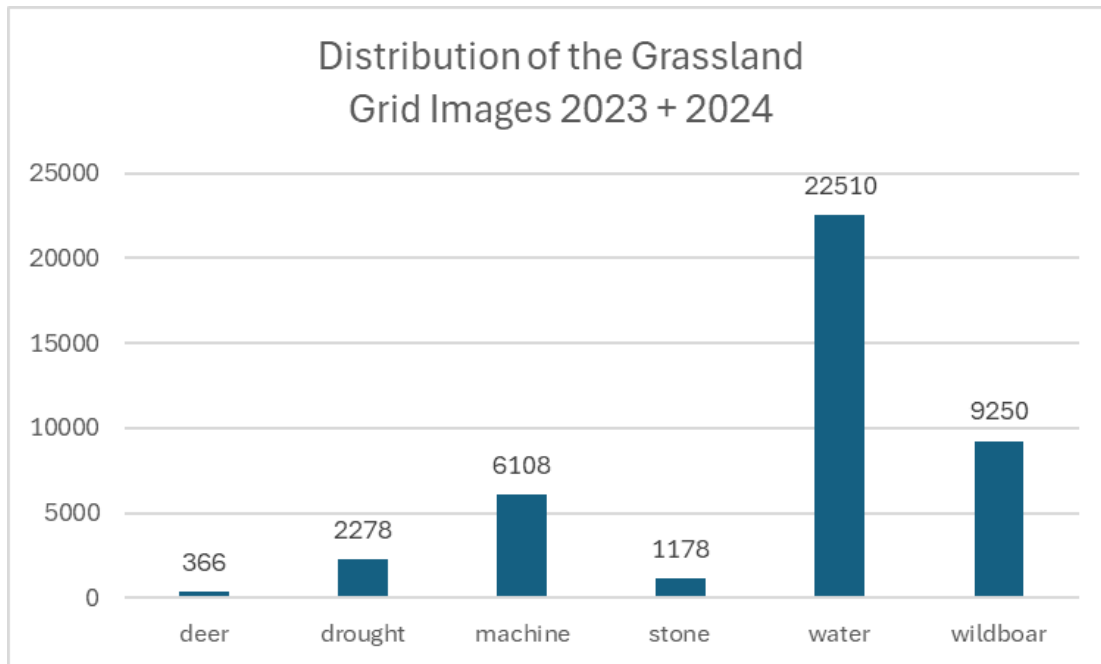
<b>1. Data Preprocessing + Model Fitting Results .....</b>	<b>69</b>
1.1 Data Distribution	69
1.2 Model Fitting Results	70
<b>2. Results 2024 Grass - Validation polygons evaluation .....</b>	<b>70</b>
Total 2024	70
Total, 2024: GRID validation polygon evaluation .....	70
Total, 2024: NO-GRID validation polygon evaluation .....	71
Blekinge 2024	72
Blekinge, 2024: GRID validation polygon evaluation .....	72
Blekinge, 2024: NO-GRID validation polygon evaluation .....	73
Jönköping 2024	74
Jönköping, 2024: GRID validation polygon evaluation .....	74
Jönköping, 2024: NO-GRID validation polygon evaluation .....	75
Örebro 2024	76
Örebro, 2024: GRID validation polygon evaluation .....	76
Örebro, 2024: NO-GRID validation polygon evaluation .....	77
Södermanland 2024	78
Södermanland, 2024: GRID validation polygon evaluation .....	78
Södermanland, 2024: NO-GRID validation polygon evaluation .....	79
<b>3. Results 2024 - Field Prediction Evaluation .....</b>	<b>80</b>
Grassland – Grass-fitted model	80
Overlapping areas of validation polygons and created damage polygons .....	80
Field evaluation Grassland Grid / No-grid Blekinge 2024 .....	80
Overlapping areas of validation polygons and created damage polygons .....	81
Field evaluation Grassland Grid / No-grid Jönköping 2024 .....	81
Overlapping areas of validation polygons and created damage polygons .....	82
Field evaluation Grassland Grid / No-grid Örebro 2024 .....	82
Overlapping areas of validation polygons and created damage polygons .....	83

Field evaluation Grassland Grid / No-grid Södermanland 2024 .....	83
<b>4. Post-classification Analysis – Damage Types ratios .....</b>	<b>84</b>
Grassland – Jönköping damage types ratios	84
Grassland - Object-based Random Forest Damage Classification .....	84
Grassland Object-based Support Vector Machine Damage Classification.....	85
Grassland Pixel-based Random Forest Damage Classification .....	87
Grassland Pixel-based Support Vector Machine Damage Classification.....	88
Grassland – Blekinge damage types ratios	89
Grassland - Object-based Random Forest Damage Classification .....	89
Grassland Object-based Support Vector Machine Damage Classification.....	91
Grassland Pixel-based Random Forest Damage Classification .....	92
Grassland Pixel-based Support Vector Machine Damage Classification.....	93
Grassland – Örebro damage types ratios	95
Grassland - Object-based Random Forest Damage Classification .....	95
Grassland Object-based Support Vector Machine Damage Classification.....	96
Grassland Pixel-based Random Forest Damage Classification .....	98
Grassland Pixel-based Support Vector Machine Damage Classification.....	99
Grassland – Södermanland damage types ratios	101
Grassland - Object-based Random Forest Damage Classification .....	101
Grassland Object-based Support Vector Machine Damage Classification.....	102
Grassland Pixel-based Random Forest Damage Classification .....	104
Grassland Pixel-based Support Vector Machine Damage Classification.....	106

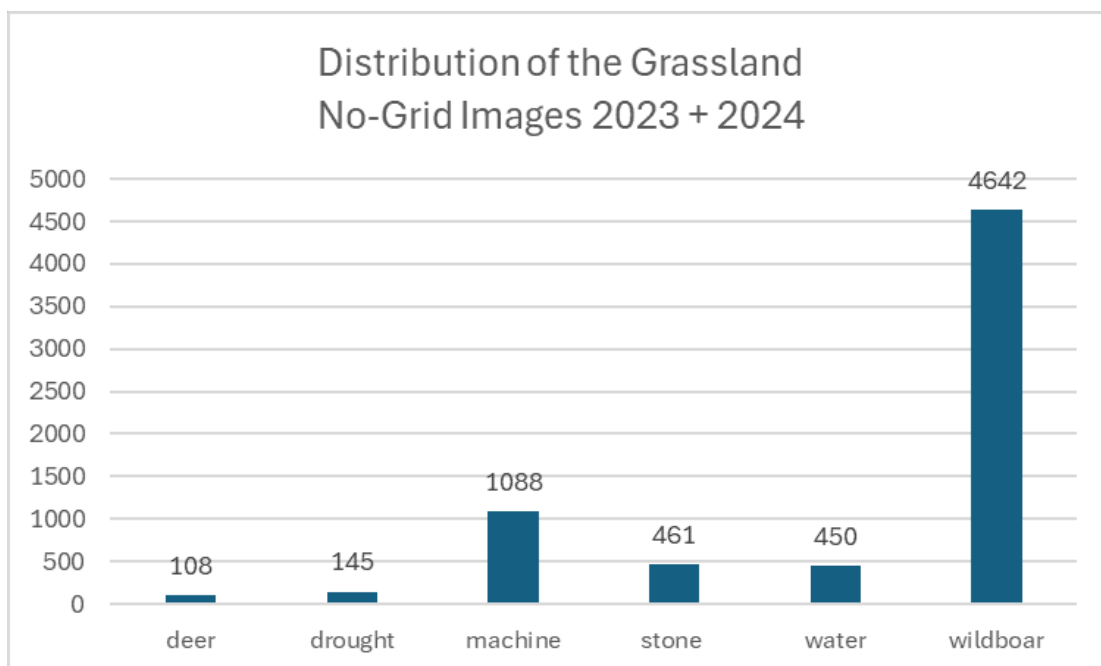
# 1. Data Preprocessing + Model Fitting Results

## 1.1 Data Distribution

Given the distribution of the grassland grid images created from 2023 and 2024 validation polygons (Figure 1 and 2), it was decided to perform 2 augmentations on machine and wild boar, and 5 augmentations on deer, drought, and stone. For the no-grid images, it was decided to perform 3 augmentations on machine and 5 augmentations on deer, drought, stone, and water.



**Figure 15.** Distribution of the grid-based images created from the 2023 and 2024 validation polygons data of grassland.



**Figure 16.** Distribution of the no-grid-based images created from the 2023 and 2024 validation polygons data of grassland.

## 1.2 Model Fitting Results

**Table 1.** Result of the fitting of the grass-fitted model using the grid/no-grid augmented images.

<i>Grid</i>	<i>Epo chs</i>	<i>Val acc</i>	<i>Train acc</i>	<i>Val loss</i>	<i>Train loss</i>	<i>No- Grid</i>	<i>Epo chs</i>	<i>Val acc</i>	<i>Train acc</i>	<i>Val loss</i>	<i>Train loss</i>
Grass	57	0.71	0.73	<b>0.81</b>	0.74	Grass	150	0.75	0.75	0.69	0.69

## 2. Results 2024 Grass - Validation polygons evaluation

### Total 2024

#### Total, 2024: GRID validation polygon evaluation

Total instances predicted: 32460

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

#### Confusion Matrix:

<i>TRUE</i>							
		deer	drought	machine	stone	water	Wild boar
<i>PRED</i>	deer	0.45%	0.04%	0.02%	0.01%	0.09%	0.03%
	drought	0.01%	0.86%	0.12%	0.05%	0.25%	0.07%
	machine	0.05%	0.20%	7.25%	0.25%	1.38%	0.63%
	stone	0.00%	0.03%	0.06%	1.11%	0.06%	0.10%
	water	0.43%	2.46%	7.01%	0.94%	62.43%	2.59%
	wild boar	0.12%	0.51%	1.46%	0.81%	3.30%	4.82%
total True		1.07%	4.09%	15.91%	3.17%	67.52%	8.23%
Instances		347	1329	5166	1029	21918	2671

#### Overall performance:

<i>Total Accuracy</i>	<i>Total Kappa</i>	<i>Average Precision</i>	<i>Average Recall</i>	<i>Average F1score</i>
0.77	0.50	0.49	0.69	0.54

#### Class performance:

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
Deer	0.70	0.42	0.52
Drought	0.63	0.21	0.32
Machine	0.74	0.46	0.56
Stone	0.81	0.35	0.49
Water	0.82	0.92	0.87
Wild boar	0.44	0.59	0.50

## Total, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 2657

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

### Confusion Matrix:

<i>TRUE</i>							
<i>PRED</i>		deer	drought	machine	stone	water	Wild boar
	deer	3.20%	0.04%	0.38%	0.08%	0.00%	1.02%
	drought	0.00%	3.09%	0.23%	0.08%	0.19%	0.68%
	machine	0.08%	0.11%	26.42%	0.11%	1.32%	4.78%
	stone	0.08%	0.15%	0.75%	12.53%	0.15%	7.38%
	water	0.00%	0.11%	0.53%	0.11%	11.29%	1.69%
	wild boar	0.11%	0.08%	1.62%	2.22%	0.49%	18.93%
	total True Instances	3.46%	3.58%	29.92%	15.13%	13.44%	34.47%
		92	95	795	402	357	916

### Overall performance:

<i>Total Accuracy</i>	<i>Total Kappa</i>	<i>Average Precision</i>	<i>Average Recall</i>	<i>Average F1score</i>
0.75	0.68	0.81	0.74	0.77

### Class performance:

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
Deer	0.68	0.92	0.78
Drought	0.73	0.86	0.79
Machine	0.81	0.88	0.84
Stone	0.60	0.83	0.69
Water	0.82	0.84	0.83
Wild boar	0.81	0.55	0.65

Blekinge 2024

Blekinge, 2024: GRID validation polygon evaluation

Total instances predicted: 3253

Number of fields evaluated: 38

Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.00%	0.06%	0.06%	0.03%	0.09%	0.12%
drought	0.00%	1.63%	0.09%	0.22%	0.03%	0.06%
machine	0.00%	0.52%	19.43%	0.74%	1.29%	1.66%
stone	0.00%	0.00%	0.06%	5.53%	0.00%	0.40%
water	0.00%	5.81%	7.22%	3.07%	22.75%	7.56%
wild boar	0.00%	1.54%	2.71%	3.54%	2.77%	11.01%
total True	0.00%	9.56%	29.57%	13.13%	26.93%	20.81%
Instances	0	311	962	427	876	677

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.60	0.04	0.47	0.03

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0	0	/	/	/	/
Drought	0.80	0.19	0.17	0.01	0.28	0.02
Machine	0.82	0.17	0.66	0.08	0.73	0.05
Stone	0.92	0.15	0.42	0.06	0.58	0.04
Water	0.49	0.12	0.84	0.03	0.62	0.04
Wild boar	0.51	0.19	0.53	0.05	0.52	0.04



## Blekinge, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 393

Number of fields evaluated: 38

### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.00%	0.00%	0.00%	0.00%	0.00%	0.25%
drought	0.00%	3.82%	0.00%	0.00%	0.00%	1.02%
machine	0.00%	0.25%	17.81%	0.51%	0.00%	1.78%
stone	0.00%	0.00%	0.25%	32.57%	0.00%	4.33%
water	0.00%	0.51%	0.25%	0.00%	4.33%	2.54%
wild boar	0.00%	0.25%	0.00%	6.87%	0.25%	22.39%
total True	0.00%	4.83%	18.32%	39.95%	4.58%	32.32%
Instances	0	19	72	157	18	127

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.81	0.02	0.73	0.08

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0	0	/	/	/	/
Drought	0.79	0.20	0.79	0.13	0.79	0
Machine	0.88	0.14	0.97	0	0.92	0.01
Stone	0.88	0.13	0.82	0.04	0.84	0.03
Water	0.57	0.25	0.94	0.01	0.71	0
Wild boar	0.75	0.14	0.69	0.09	0.72	0.03

## Jönköping 2024

### Jönköping, 2024: GRID validation polygon evaluation

Total instances predicted: 5147

Number of fields evaluated: 42

#### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.00%	0.00%	0.08%	0.04%	0.16%	0.06%
drought	0.00%	2.68%	0.45%	0.16%	0.21%	0.33%
machine	0.00%	0.76%	14.42%	0.70%	1.75%	2.08%
stone	0.00%	0.17%	0.19%	2.02%	0.04%	0.14%
water	0.00%	3.05%	13.72%	1.92%	30.17%	3.85%
wild boar	0.00%	1.22%	3.28%	1.34%	3.48%	11.54%
total True	0.00%	7.89%	32.14%	6.18%	35.81%	17.99%
Instances	0	406	1654	318	1843	926

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.61	0.07	0.45	0.02

#### Class performance:

	Variance		Variance		Variance	
	Precision	Precision	Recall	Recall	F1score	F1score
Deer	0	0	/	/	/	/
Drought	0.70	0.18	0.34	0.06	0.46	0.06
Machine	0.73	0.16	0.45	0.07	0.56	0.06
Stone	0.79	0.14	0.33	0.06	0.46	0.05
Water	0.57	0.11	0.84	0.02	0.68	0.07
Wild boar	0.55	0.13	0.64	0.07	0.59	0.07

## Jönköping, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 1050

Number of fields evaluated: 42

### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.00%	0.10%	0.86%	0.19%	0.00%	2.29%
drought	0.00%	4.38%	0.48%	0.10%	0.10%	1.24%
machine	0.00%	0.19%	27.81%	0.10%	0.67%	7.05%
stone	0.00%	0.29%	0.76%	11.90%	0.19%	9.14%
water	0.00%	0.10%	0.67%	0.10%	6.29%	1.33%
wild boar	0.00%	0.00%	1.90%	0.95%	0.48%	20.38%
total True	0.00%	5.05%	32.48%	13.33%	7.71%	41.43%
Instances	0	53	341	140	81	435

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.71	0.04	0.61	0.08

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0	0	/	/	/	/
Drought	0.70	0.22	0.87	0.08	0.77	0
Machine	0.78	0.11	0.86	0.01	0.81	0.03
Stone	0.53	0.18	0.89	0.02	0.67	0.06
Water	0.74	0.20	0.81	0.08	0.78	0.01
Wild boar	0.86	0.22	0.49	0.06	0.63	0.03

# Örebro 2024

## Örebro, 2024: GRID validation polygon evaluation

Total instances predicted: 11423

Number of fields evaluated: 43

### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	1.21%	0.10%	0.00%	0.00%	0.06%	0.00%
drought	0.04%	0.60%	0.03%	0.00%	0.14%	0.01%
machine	0.11%	0.03%	6.06%	0.11%	1.48%	0.14%
stone	0.00%	0.00%	0.03%	0.32%	0.07%	0.02%
water	0.95%	1.81%	5.40%	0.56%	73.68%	1.52%
wild boar	0.26%	0.29%	0.99%	0.32%	2.07%	1.60%
total True	2.57%	2.83%	12.50%	1.31%	77.49%	3.29%
Instances	294	323	1428	150	8852	376

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.83	0.01	0.51	0.03

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.88	0.23	0.47	0.04	0.61	0.01
Drought	0.74	0.20	0.21	0	0.33	0.01
Machine	0.76	0.13	0.48	0.08	0.59	0.06
Stone	0.74	0.19	0.25	0.11	0.37	0.07
Water	0.88	0.14	0.95	0.02	0.91	0.05
Wild boar	0.29	0.10	0.49	0.07	0.36	0.04

Örebro, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 680

Number of fields evaluated: 43

Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	9.26%	0.00%	0.00%	0.00%	0.00%	0.15%
drought	0.00%	1.32%	0.00%	0.15%	0.44%	0.00%
machine	0.15%	0.00%	30.74%	0.00%	3.38%	4.26%
stone	0.00%	0.00%	0.44%	5.15%	0.15%	5.88%
water	0.00%	0.00%	0.44%	0.29%	16.62%	1.03%
wild boar	0.15%	0.00%	1.62%	1.32%	0.59%	16.47%
total True	9.56%	1.32%	33.24%	6.91%	21.18%	27.79%
Instances	65	9	226	47	144	189

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.80	0.04	0.73	0.07

Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.98	0.08	0.97	0	0.98	0
Drought	0.69	0.25	1	0	0.82	0
Machine	0.80	0.11	0.92	0.13	0.86	0.02
Stone	0.44	0.17	0.74	0.09	0.56	0.07
Water	0.90	0.04	0.78	0.07	0.84	0.03
Wild boar	0.82	0.22	0.59	0.07	0.69	0.04

## Södermanland 2024

### Södermanland, 2024: GRID validation polygon evaluation

Total instances predicted: 12632

Number of fields evaluated: 46

#### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.06%	0.00%	0.00%	0.01%	0.09%	0.02%
drought	0.00%	0.16%	0.08%	0.01%	0.43%	0.02%
machine	0.03%	0.04%	2.26%	0.06%	1.17%	0.21%
stone	0.01%	0.01%	0.02%	0.32%	0.09%	0.08%
water	0.25%	1.91%	5.68%	0.34%	75.66%	1.76%
wild boar	0.08%	0.14%	0.83%	0.33%	4.47%	3.40%
total True	0.42%	2.26%	8.87%	1.06%	81.91%	5.48%
Instances	53	285	1121	134	10347	692

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.82	0.08	0.38	0.02

#### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.33	0.22	0.13	0.01	0.19	0.01
Drought	0.23	0.21	0.07	0	0.11	0
Machine	0.60	0.16	0.26	0.05	0.36	0.04
Stone	0.61	0.19	0.30	0.07	0.40	0.04
Water	0.88	0.18	0.92	0.02	0.90	0.07
Wild boar	0.37	0.11	0.62	0.09	0.46	0.05

## Södermanland, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 534

Number of fields evaluated: 45

### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	4.12%	0.00%	0.19%	0.00%	0.00%	0.19%
drought	0.00%	2.25%	0.19%	0.00%	0.19%	0.19%
machine	0.19%	0.00%	24.53%	0.00%	0.94%	3.18%
stone	0.37%	0.19%	1.50%	8.43%	0.19%	8.05%
water	0.00%	0.00%	0.56%	0.00%	19.48%	2.62%
wild boar	0.37%	0.19%	2.25%	2.43%	0.56%	16.67%
total True	5.06%	2.62%	29.21%	10.86%	21.35%	30.90%
Instances	27	14	156	58	114	165

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.75	0.05	0.68	0.08

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.92	0.20	0.81	0.13	0.86	0.02
Drought	0.80	0.18	0.86	0.12	0.83	0.02
Machine	0.85	0.14	0.84	0.09	0.85	0.02
Stone	0.45	0.19	0.78	0.10	0.57	0.04
Water	0.86	0.11	0.91	0.07	0.89	0.02
Wild boar	0.74	0.18	0.54	0.14	0.63	0.05

### 3. Results 2024 - Field Prediction Evaluation

#### Grassland – Grass-fitted model

#### Overlapping areas of validation polygons and created damage polygons

<b>Blekinge Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	0	0	0	0	0	0	0	0
Drought	665	644	925	727	288	304	328	223
Machine	2182	2195	2191	2191	1676	1675	1279	1324
Stone	390	391	389	388	369	371	361	362
Water	2300	2200	2214	1943	1037	1093	655	524
Wild boar	1495	1495	1485	1484	1195	1219	936	902

#### Field evaluation Grassland Grid / No-grid Blekinge 2024

##### Blekinge 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.54	0.35	0.34	0.46	0.35	0.40	0.39	0.45
Object SVM	0.54	0.35	0.33	0.46	0.35	0.40	0.39	0.45
Pixel RF	0.52	0.33	0.33	0.46	0.35	0.39	0.39	0.44
Pixel SVM	0.51	0.33	0.33	0.45	0.34	0.39	0.39	0.45

##### Blekinge 2024. No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.30	0.09	0.03	0.32	0.22	0.26	0.06	0.14
Object SVM	0.39	0.19	0.00	0.27	0.26	0.26	0.29	0.32
Pixel RF	0.36	0.17	0.09	0.35	0.29	0.31	0.19	0.30
Pixel SVM	0.28	0.08	0.07	0.34	0.22	0.27	0.17	0.34



## Overlapping areas of validation polygons and created damage polygons

<b>Jönköping Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	0	0	0	0	0	0	0	0
Drought	769	750	782	709	458	446	373	330
Machine	2737	2740	2697	2435	2078	2035	1778	1670
Stone	329	329	328	324	294	294	279	272
Water	5276	5185	5215	4810	3893	3666	3424	2784
Wild boar	1033	1004	1066	939	800	793	732	618

## Field evaluation Grassland Grid / No-grid Jönköping 2024

### Jönköping 2024. Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.63	0.42	0.48	0.43	0.46	0.37	0.68	0.48
Object SVM	0.63	0.42	0.48	0.43	0.46	0.36	0.67	0.47
Pixel RF	0.63	0.42	0.49	0.44	0.46	0.38	0.69	0.49
Pixel SVM	0.64	0.43	0.49	0.45	0.47	0.37	0.70	0.48

### Jönköping 2024. No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.53	0.28	0.35	0.33	0.34	0.27	0.63	0.38
Object SVM	0.60	0.36	0.35	0.31	0.33	0.29	0.60	0.39
Pixel RF	0.64	0.38	0.46	0.36	0.41	0.54	0.56	0.55
Pixel SVM	0.70	0.54	0.46	0.44	0.45	0.57	0.65	0.60

## Overlapping areas of validation polygons and created damage polygons

<b>Örebro Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	497	439	522	534	270	233	183	203
Drought	1175	1176	1215	1221	846	863	682	818
Machine	1621	1626	1589	1511	1202	1196	1121	1058
Stone	144	144	144	144	141	141	136	135
Water	35822	34733	36605	34095	25577	24443	22559	17021
Wild boar	293	293	291	284	232	240	230	209

## Field evaluation Grassland Grid / No-grid Örebro 2024

### Örebro 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.87	0.31	0.38	0.40	0.42	0.41	0.45	0.07
Object SVM	0.86	0.31	0.37	0.40	0.42	0.41	0.45	0.07
Pixel RF	0.87	0.31	0.37	0.39	0.42	0.41	0.45	0.07
Pixel SVM	0.87	0.31	0.37	0.40	0.43	0.42	0.45	0.07

### Örebro 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.58	0.02	-0.03	0.24	0.25	0.24	0.41	0.02
Object SVM	0.40	-0.03	-0.03	0.28	0.20	0.23	0.34	0.03
Pixel RF	0.77	0.13	-0.01	0.30	0.29	0.30	0.31	0.06
Pixel SVM	0.63	0.05	0.00	0.30	0.29	0.29	0.27	0.05

## Overlapping areas of validation polygons and created damage polygons

<b>Södermanland Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	24	25	24	22	19	19	15	12
Drought	827	890	895	921	426	475	360	439
Machine	1627	1626	1621	1619	1236	1296	1093	1180
Stone	110	111	110	110	108	108	107	107
Water	49030	48629	47526	45066	24728	24425	17204	17404
Wild boar	1359	1360	1360	1362	1248	1259	1168	1209

## Field evaluation Grassland Grid / No-grid Södermanland 2024

### Södermanland 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.83	0.18	0.27	0.24	0.34	0.28	0.43	0.14
Object SVM	0.83	0.18	0.26	0.24	0.34	0.28	0.43	0.14
Pixel RF	0.82	0.18	0.27	0.24	0.34	0.28	0.43	0.15
Pixel SVM	0.82	0.18	0.26	0.24	0.34	0.28	0.42	0.15

### Södermanland 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.71	0.04	-0.06	0.19	0.28	0.23	0.03	0.02
Object SVM	0.69	0.03	-0.07	0.18	0.27	0.22	0.03	0.02
Pixel RF	0.59	0.03	-0.01	0.19	0.31	0.24	0.08	0.04
Pixel SVM	0.45	-0.03	-0.03	0.18	0.28	0.22	0.04	0.01

## 4. Post-classification Analysis – Damage Types ratios

### Grassland – Jönköping damage types ratios

#### Grassland - Object-based Random Forest Damage Classification

**Table 2.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	223426m <sup>2</sup>	2429m <sup>2</sup>	2311m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 3.** The ratio between the total area of predicted damage (by classification 1. Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.25</b>	0.21	0.02

**Table 4.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.2	0.13	0.07	0.19	0.02	0.57
<b>NO-GRID - Mean</b>	0.16	0.05	0.06	0.17	0.15	0.55
<b>GRID - Median</b>	0.15	0	0	0.16	0.01	0.6
<b>NO-GRID - Median</b>	0.08	0.03	0.03	0.14	0	0.6
<b>GRID - Variance</b>	0.02	0.58	0.26	0.02	0	0.05
<b>NO-GRID - Variance</b>	0.05	0.01	0.01	0.02	1.04	0.06

**Table 5.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.63	0.58	0.04	0.07	0.13
<b>NO-GRID - Mean</b>	0.02	0.01	0.01	0.02	0.69	0.1
<b>GRID - Median</b>	0.02	0	0	0.02	0	0.07
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.05
<b>GRID - Variance</b>	0	3.45	3.69	0	0.36	0.02
<b>NO-GRID - Variance</b>	0	0	0	0	4.44	0.02

**Table 6.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.201	0.01	0.01	0.19	0.01	0.58
<b>NO-GRID - Mean</b>	0.116	0.04	0.07	0.16	0	0.61

**Table 7.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.033	0	0	0.03	0	0.1	0.84
<b>NO-GRID - Mean</b>	0.014	0.01	0.01	0.02	0	0.07	0.88

## Grassland Object-based Support Vector Machine Damage Classification

**Table 8.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	170841m <sup>2</sup>	1857m <sup>2</sup>	1682m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 9.** The ratio between the total area of predicted damage (by classification 1. Object-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.21</b>	0.17	0.02

**Table 10.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.19	0.07	0.2	0.19	0.02	0.58
<b>NO-GRID - Mean</b>	0.17	0.08	0.04	0.18	0.09	0.53
<b>GRID - Median</b>	0.15	0	0	0.16	0.01	0.59
<b>NO-GRID - Median</b>	0.09	0.03	0.02	0.16	0	0.57
<b>GRID - Variance</b>	0.02	0.21	1.52	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.04	0.01	0.01	0.02	0.5	0.05

**Table 11.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.63	0.35	0.03	0.1	0.1
<b>NO-GRID - Mean</b>	0.02	0.01	0	0.02	0.54	0.08
<b>GRID - Median</b>	0.02	0	0	0.02	0	0.06
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.05
<b>GRID - Variance</b>	0	3.57	1.98	0	0.59	0.01
<b>NO-GRID - Variance</b>	0	0	0	0	3.19	0.01

**Table 12.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.183	0.01	0.02	0.18	0.02	0.59
<b>NO-GRID - Mean</b>	0.145	0.05	0.03	0.16	0.01	0.6

**Table 13.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.023	0	0	0.02	0	0.07	0.87
<b>NO-GRID - Mean</b>	0.013	0.01	0	0.01	0	0.06	0.91

## Grassland Pixel-based Random Forest Damage Classification

**Table 14.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	160277m <sup>2</sup>	1742m <sup>2</sup>	1935m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 15.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.17</b>	0.1	0.03

**Table 16.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.15	0.03	0.17	0.02	0.63
<b>NO-GRID - Mean</b>	0.21	0.04	0.04	0.26	0.2	0.53
<b>GRID - Median</b>	0.11	0	0	0.13	0.01	0.64
<b>NO-GRID - Median</b>	0.09	0.01	0.01	0.25	0.01	0.51
<b>GRID - Variance</b>	0.02	0.97	0.06	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.8	0.01	0.01	0.02	1.63	0.05

**Table 17.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.51	0.63	0.02	0.43	0.11
<b>NO-GRID - Mean</b>	0.08	0.39	0.25	0.02	0.78	0.09
<b>GRID - Median</b>	0.01	0	0	0.01	0	0.05
<b>NO-GRID - Median</b>	0	0	0	0.02	0	0.03
<b>GRID - Variance</b>	0	2.75	3.6	0	3.27	0.02
<b>NO-GRID - Variance</b>	0.48	3.37	1.55	0	4.63	0.03

**Table 18.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.143	0.01	0.01	0.14	0.01	0.68
<b>NO-GRID - Mean</b>	0.073	0.02	0.05	0.2	0.01	0.65

**Table 19.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.017	0	0	0.02	0	0.08	0.88
<b>NO-GRID - Mean</b>	0.006	0	0	0.02	0	0.06	0.91

## Grassland Pixel-based Support Vector Machine Damage Classification

**Table 20.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	57006m <sup>2</sup>	620m <sup>2</sup>	906m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 21.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.06</b>	<b>0.03</b>	<b>0</b>

**Table 22.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.18	0.06	0.1	0.19	0.04	0.58
<b>NO-GRID - Mean</b>	0.17	0.02	0.05	0.32	0.06	0.38
<b>GRID - Median</b>	0.13	0	0	0.14	0.01	0.59
<b>NO-GRID - Median</b>	0.1	0	0.01	0.28	0.02	0.39
<b>GRID - Variance</b>	0.03	0.32	0.63	0.03	0	0.06
<b>NO-GRID - Variance</b>	0.03	0	0.01	0.04	0.01	0.06



**Table 23.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.01	0.89	0.44	0.07	0.9	0.03
<b>NO-GRID - Mean</b>	0.06	1.27	0.34	0.01	0.41	0.07
<b>GRID - Median</b>	0	0	0	0	0	0.01
<b>NO-GRID - Median</b>	0	0	0	0.01	0	0.01
<b>GRID - Variance</b>	0	4.15	2.36	0.31	5.32	0
<b>NO-GRID - Variance</b>	0.17	6.43	2.39	0	2.85	0.28

**Table 24.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.02	0.01	0.17	0.02	0.62
<b>NO-GRID - Mean</b>	0.12	0.02	0.05	0.3	0.02	0.49

**Table 25.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.007	0	0	0.01	0	0.03	0.96
<b>NO-GRID - Mean</b>	0.004	0	0	0.01	0	0.02	0.97

## Grassland – Blekinge damage types ratios

### Grassland - Object-based Random Forest Damage Classification

**Table 26.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	153982m <sup>2</sup>	2139m <sup>2</sup>	1772m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 27.** The ratio between the total area of predicted damage (by classification 1. Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.28</b>	0.22	0.06

**Table 28.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.21	0.01	0.02	0.17	0.03	0.56
<b>NO-GRID - Mean</b>	0.14	0.03	0.08	0.15	0.09	0.59
<b>GRID - Median</b>	0.18	0	0	0.1	0.01	0.55
<b>NO-GRID - Median</b>	0.09	0.02	0.02	0.12	0	0.63
<b>GRID - Variance</b>	0.02	0	0	0.03	0	0.04
<b>NO-GRID - Variance</b>	0.03	0	0.01	0.02	0.48	0.05

**Table 29.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.06	0.48	0.5	0.04	0.12	0.13
<b>NO-GRID - Mean</b>	0.03	0.11	0.01	0.02	0.7	0.11
<b>GRID - Median</b>	0.03	0	0	0.02	0	0.1
<b>NO-GRID - Median</b>	0.01	0	0	0.02	0	0.06
<b>GRID - Variance</b>	0.02	2.97	3.54	0	0.43	0.01
<b>NO-GRID - Variance</b>	0	0.86	0	0	4.79	0.02

**Table 30.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.206	0.01	0.01	0.22	0.04	0.52
<b>NO-GRID - Mean</b>	0.194	0.04	0.06	0.16	0.01	0.55

**Table 31.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.035	0	0	0.04	0.01	0.09	0.83
<b>NO-GRID - Mean</b>	0.025	0	0.01	0.02	0	0.07	0.87

## Grassland Object-based Support Vector Machine Damage Classification

**Table 32.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	153283m <sup>2</sup>	2129m <sup>2</sup>	1774m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 33.** The ratio between the total area of predicted damage (by classification 1. Object-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.27</b>	0.22	0.06

**Table 34.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.21	0.12	0.02	0.16	0.03	0.57
<b>NO-GRID - Mean</b>	0.15	0.04	0.06	0.17	0.01	0.58
<b>GRID - Median</b>	0.17	0	0	0.09	0.01	0.57
<b>NO-GRID - Median</b>	0.08	0.02	0.02	0.09	0	0.65
<b>GRID - Variance</b>	0.02	0.45	0	0.03	0	0.04
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.03	0	0.06

**Table 35.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.06	0.73	0.32	0.03	0.12	0.13
<b>NO-GRID - Mean</b>	0.03	0.18	0.01	0.03	0.59	0.11
<b>GRID - Median</b>	0.03	0	0	0.02	0	0.1
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.07
<b>GRID - Variance</b>	0.02	4.49	1.99	0	0.35	0.01
<b>NO-GRID - Variance</b>	0	1.08	0	0	3.37	0.02

**Table 36.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.214	0.02	0.02	0.2	0.04	0.52
<b>NO-GRID - Mean</b>	0.206	0.03	0.04	0.17	0.01	0.55

**Table 37.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.036	0	0	0.03	0.01	0.09	0.83
<b>NO-GRID - Mean</b>	0.027	0	0	0.02	0	0.07	0.87

## Grassland Pixel-based Random Forest Damage Classification

**Table 38.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	95349m <sup>2</sup>	1324m <sup>2</sup>	1136m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 39.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.17</b>	0.12	0.03

**Table 40.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.19	0.21	0.02	0.16	0.15	0.59
<b>NO-GRID - Mean</b>	0.18	0.01	0.09	0.27	0.02	0.43
<b>GRID - Median</b>	0.16	0	0	0.09	0.01	0.62
<b>NO-GRID - Median</b>	0.11	0	0.03	0.21	0.01	0.46
<b>GRID - Variance</b>	0.01	1.61	0	0.03	1.06	0.04
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.04	0	0.06

**Table 41.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.76	0.14	0.02	0.32	0.09
<b>NO-GRID - Mean</b>	0.03	0.28	0.14	0.03	0.27	0.04
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.06
<b>NO-GRID - Median</b>	0.01	0	0	0.02	0	0.03
<b>GRID - Variance</b>	0	3.09	0.46	0	2.01	0.01
<b>NO-GRID - Variance</b>	0	1.22	1.18	0	1.79	0

**Table 42.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.196	0.01	0.02	0.19	0.02	0.56
<b>NO-GRID - Mean</b>	0.224	0.02	0.08	0.29	0.01	0.38

**Table 43.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.021	0	0	0.02	0	0.06	0.89
<b>NO-GRID - Mean</b>	0.017	0	0.01	0.02	0	0.03	0.92

## Grassland Pixel-based Support Vector Machine Damage Classification

**Table 44.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	80792m <sup>2</sup>	1122m <sup>2</sup>	1119m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 45.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.15</b>	<b>0.1</b>	<b>0.02</b>

**Table 46.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.21	0.05	0.09	0.16	0.18	0.58
<b>NO-GRID - Mean</b>	0.18	0.01	0.09	0.25	0.03	0.44
<b>GRID - Median</b>	0.17	0	0	0.08	0.01	0.6
<b>NO-GRID - Median</b>	0.13	0	0.02	0.2	0.01	0.46
<b>GRID - Variance</b>	0.02	0.14	0.35	0.04	1.03	0.05
<b>NO-GRID - Variance</b>	0.03	0	0.02	0.04	0	0.06

**Table 47.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.73	0.58	0.02	0.72	0.08
<b>NO-GRID - Mean</b>	0.13	1.18	0.01	0.02	0.12	0.05
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.05
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.02
<b>GRID - Variance</b>	0	4.04	3.82	0	4.74	0.01
<b>NO-GRID - Variance</b>	0.83	6.69	0	0	0.7	0

**Table 48.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.204	0.01	0.03	0.18	0.03	0.55
<b>NO-GRID - Mean</b>	0.195	0.01	0.07	0.25	0.01	0.46

**Table 49.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.018	0	0	0.02	0	0.05	0.91
<b>NO-GRID - Mean</b>	0.013	0	0	0.02	0	0.03	0.93

## Grassland – Örebro damage types ratios

### Grassland - Object-based Random Forest Damage Classification

**Table 50.** The total fields predicted in Örebro. together with the total area. and mean and standard deviation of the grass fields in Örebro. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	429866m <sup>2</sup>	4525m <sup>2</sup>	5040m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 51.** The ratio between the total area of predicted damage (by classification 1. Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.24	0.05

**Table 52.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.13	0.25	0.18	0.11	0.11	0.73
<b>NO-GRID - Mean</b>	0.12	0.14	0.13	0.11	0.24	0.59
<b>GRID - Median</b>	0.11	0	0	0.07	0	0.78
<b>NO-GRID - Median</b>	0.05	0.01	0.04	0.09	0	0.62
<b>GRID - Variance</b>	0.01	1.3	1.4	0.02	1.01	0.04
<b>NO-GRID - Variance</b>	0.04	0.93	0.05	0.01	1.67	0.07

**Table 53.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.85	0.18	0.02	0.26	0.22
<b>NO-GRID - Mean</b>	0.03	0.22	0.13	0.01	0.42	0.13
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.16
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.08
<b>GRID - Variance</b>	0	5.23	0.92	0.01	1.97	0.03
<b>NO-GRID - Variance</b>	0.01	1.21	0.67	0	1.78	0.02

**Table 54.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.091	0	0.01	0.09	0.01	0.79
<b>NO-GRID - Mean</b>	0.181	0.01	0.21	0.09	0.01	0.49

**Table 55.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0	0.02	0	0.17	0.78
<b>NO-GRID - Mean</b>	0.033	0	0.04	0.02	0	0.09	0.82

## Grassland Object-based Support Vector Machine Damage Classification

**Table 56.** The total fields predicted in Örebro. together with the total area. and mean and standard deviation of the grass fields in Örebro. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	407910m <sup>2</sup>	4294m <sup>2</sup>	4775m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 57.** The ratio between the total area of predicted damage (by classification 1. Object-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.26	0.05

**Table 58.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.13	0.42	0.11	0.12	0.1	0.72
<b>NO-GRID - Mean</b>	0.14	0.12	0.12	0.12	0.15	0.66
<b>GRID - Median</b>	0.11	0	0	0.07	0	0.77
<b>NO-GRID - Median</b>	0.06	0.02	0.03	0.08	0	0.61
<b>GRID - Variance</b>	0.01	2.85	1	0.02	0.75	0.04
<b>NO-GRID - Variance</b>	0.05	0.23	0.05	0.01	0.9	0.61



**Table 59.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	1.28	0.36	0.02	0.24	0.21
<b>NO-GRID - Mean</b>	0.04	0.37	0.06	0.01	0.82	0.2
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.14
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.08
<b>GRID - Variance</b>	0	6.8	2.74	0.01	1.73	0.04
<b>NO-GRID - Variance</b>	0.01	2.38	0.06	0	4.83	0.5

**Table 60.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.096	0	0.01	0.1	0.01	0.79
<b>NO-GRID - Mean</b>	0.197	0.01	0.2	0.1	0	0.49

**Table 61.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0	0.02	0	0.16	0.79
<b>NO-GRID - Mean</b>	0.034	0	0.03	0.02	0	0.08	0.83

## Grassland Pixel-based Random Forest Damage Classification

**Table 62.** The total fields predicted in Örebro. together with the total area. and mean and standard deviation of the grass fields in Örebro. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	328348m <sup>2</sup>	3456m <sup>2</sup>	3851m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 63.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.21</b>	0.16	0.03

**Table 64.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.11	0.43	0.01	0.11	0.07	0.74
<b>NO-GRID - Mean</b>	0.14	0.13	0.1	0.31	0.16	0.5
<b>GRID - Median</b>	0.1	0	0	0.08	0	0.77
<b>NO-GRID - Median</b>	0.08	0.01	0.03	0.2	0.01	0.49
<b>GRID - Variance</b>	0.01	2.81	0	0.02	0.31	0.03
<b>NO-GRID - Variance</b>	0.03	0.95	0.03	0.81	0.97	0.06

**Table 65.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	1.04	0.15	0.02	0.52	0.16
<b>NO-GRID - Mean</b>	0.03	0.73	0.19	0.09	0.49	0.08
<b>GRID - Median</b>	0.01	0	0	0.01	0	0.11
<b>NO-GRID - Median</b>	0.01	0	0	0.02	0	0.04
<b>GRID - Variance</b>	0	5.65	0.83	0	3.24	0.02
<b>NO-GRID - Variance</b>	0.01	4.81	0.91	0.41	2.71	0.01

**Table 66.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.088	0	0.01	0.09	0.01	0.8
<b>NO-GRID - Mean</b>	0.162	0.01	0.16	0.16	0.01	0.5

**Table 67.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.014	0	0	0.02	0	0.13	0.83
<b>NO-GRID - Mean</b>	0.019	0	0.02	0.02	0	0.06	0.88

## Grassland Pixel-based Support Vector Machine Damage Classification

**Table 68.** The total fields predicted in Örebro. together with the total area. and mean and standard deviation of the grass fields in Örebro. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	247558m <sup>2</sup>	2606m <sup>2</sup>	3485m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 69.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.11	0.03

**Table 70.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.12	0.3	0.06	0.11	0.04	0.74
<b>NO-GRID - Mean</b>	0.14	0.02	0.11	0.3	0.03	0.44
<b>GRID - Median</b>	0.1	0	0.01	0.06	0	0.78
<b>NO-GRID - Median</b>	0.08	0	0.03	0.23	0.01	0.41
<b>GRID - Variance</b>	0.01	1.75	0.16	0.02	0.03	0.03
<b>NO-GRID - Variance</b>	0.02	0	0.03	0.22	0	0.06

**Table 71.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.2	1.06	0.2	0.01	0.95	0.12
<b>NO-GRID - Mean</b>	0.12	1.05	0.24	0.06	0.26	0.06
<b>GRID - Median</b>	0.01	0	0	0.01	0	0.07
<b>NO-GRID - Median</b>	0	0	0	0.01	0	0.02
<b>GRID - Variance</b>	1.62	5.37	1.35	0	5.58	0.02
<b>NO-GRID - Variance</b>	0.42	4.92	1.4	0.14	1.27	0.01



**Table 72.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.088	0	0.02	0.09	0.01	0.79
<b>NO-GRID - Mean</b>	0.158	0.02	0.21	0.16	0.01	0.45

**Table 73.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.011	0	0	0.01	0	0.1	0.88
<b>NO-GRID - Mean</b>	0.015	0	0.02	0.02	0	0.04	0.9

## Grassland – Södermanland damage types ratios

### Grassland - Object-based Random Forest Damage Classification

**Table 74.** The total fields predicted in Södermanland. together with the total area. and mean and standard deviation of the grass fields in Södermanland. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	674233m <sup>2</sup>	7023m <sup>2</sup>	6308m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 75.** The ratio between the total area of predicted damage (by classification 1. Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.42</b>	0.3	0.76

**Table 76.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.13	0.2	0.1	0.03	0.7
<b>NO-GRID - Mean</b>	0.11	0.08	0.11	0.12	0.31	0.6
<b>GRID - Median</b>	0.13	0	0	0.08	0.01	0.73
<b>NO-GRID - Median</b>	0.08	0.03	0.06	0.09	0	0.61
<b>GRID - Variance</b>	0.01	0.63	1.66	0.01	0.02	0.03
<b>NO-GRID - Variance</b>	0.01	0.06	0.02	0.01	2.17	0.03

**Table 77.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.3	0.42	0.03	0.07	0.29
<b>NO-GRID - Mean</b>	0.03	0.1	0.05	0.04	0.72	0.17
<b>GRID - Median</b>	0.04	0	0	0.02	0	0.19
<b>NO-GRID - Median</b>	0.01	0.01	0.01	0.02	0	0.12
<b>GRID - Variance</b>	0	2.3	2.92	0	0.46	0.51
<b>NO-GRID - Variance</b>	0	0.75	0.05	0.01	3.36	0.08

**Table 78.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.157	0.01	0.01	0.11	0.01	0.7
<b>NO-GRID - Mean</b>	0.118	0.05	0.1	0.12	0	0.61

**Table 79.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.036	0	0	0.02	0	0.16	0.77
<b>NO-GRID - Mean</b>	0.022	0.01	0.02	0.02	0	0.11	0.82

## Grassland Object-based Support Vector Machine Damage Classification

**Table 80.** The total fields predicted in Södermanland. together with the total area. and mean and standard deviation of the grass fields in Södermanland. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	601624m <sup>2</sup>	6267m <sup>2</sup>	5900m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 81.** The ratio between the total area of predicted damage (by classification 1. Object-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.35</b>	0.28	0.23

**Table 82.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.15	0.13	0.1	0.03	0.7
<b>NO-GRID - Mean</b>	0.13	0.08	0.09	0.1	0.24	0.61
<b>GRID - Median</b>	0.12	0	0	0.09	0.01	0.74
<b>NO-GRID - Median</b>	0.09	0.03	0.04	0.09	0	0.62
<b>GRID - Variance</b>	0.01	0.7	0.74	0.01	0.02	0.03
<b>NO-GRID - Variance</b>	0.02	0.07	0.02	0	1.61	0.04

**Table 83.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.57	0.56	0.03	0.07	0.23
<b>NO-GRID - Mean</b>	0.03	0.29	0.11	0.02	0.75	0.15
<b>GRID - Median</b>	0.03	0	0	0.02	0	0.18
<b>NO-GRID - Median</b>	0.01	0.01	0.01	0.02	0	0.1
<b>GRID - Variance</b>	0	3.71	3.6	0	0.46	0.11
<b>NO-GRID - Variance</b>	0	2.37	0.73	0	4.2	0.03

**Table 84.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.157	0.01	0.01	0.11	0.01	0.7
<b>NO-GRID - Mean</b>	0.149	0.05	0.09	0.1	0.01	0.61

**Table 85.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.032	0	0	0.02	0	0.14	0.79
<b>NO-GRID - Mean</b>	0.024	0.01	0.02	0.02	0	0.1	0.84

## Grassland Pixel-based Random Forest Damage Classification

**Table 86.** The total fields predicted in Södermanland. together with the total area. and mean and standard deviation of the grass fields in Södermanland. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	469328m <sup>2</sup>	4889m <sup>2</sup>	5963m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 87.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.24</b>	0.18	0.12

**Table 88.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.23	0.13	0.1	0.01	0.71
<b>NO-GRID - Mean</b>	0.17	0.05	0.05	0.24	0.01	0.48
<b>GRID - Median</b>	0.11	0	0	0.09	0.01	0.74
<b>NO-GRID - Median</b>	0.14	0.03	0.03	0.23	0.01	0.47
<b>GRID - Variance</b>	0.01	1.22	0.78	0.01	0	0.03
<b>NO-GRID - Variance</b>	0.02	0	0.01	0.01	0	0.03

**Table 89.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.94	0.72	0.02	0	0.17
<b>NO-GRID - Mean</b>	0.02	0.04	0.14	0.04	0.47	0.08
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.11
<b>NO-GRID - Median</b>	0.01	0	0	0.02	0	0.05
<b>GRID - Variance</b>	0	5.48	4.04	0	0	0.09
<b>NO-GRID - Variance</b>	0	0.12	1.02	0.01	3.21	0.01

**Table 90.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.154	0.01	0.02	0.1	0.01	0.71
<b>NO-GRID - Mean</b>	0.205	0.03	0.08	0.23	0.01	0.45



**Table 91.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.025	0	0	0.02	0	0.11	0.84
<b>NO-GRID - Mean</b>	0.024	0	0.01	0.03	0	0.05	0.88

## Grassland Pixel-based Support Vector Machine Damage Classification

**Table 92.** The total fields predicted in Södermanland. together with the total area. and mean and standard deviation of the grass fields in Södermanland. of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	486479m <sup>2</sup>	5067m <sup>2</sup>	7764m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 93.** The ratio between the total area of predicted damage (by classification 1. Pixel-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.23</b>	0.17	0.06

**Table 94.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.28	0.11	0.1	0.11	0.72
<b>NO-GRID - Mean</b>	0.17	0.03	0.07	0.22	0.11	0.5
<b>GRID - Median</b>	0.12	0	0	0.07	0.01	0.76
<b>NO-GRID - Median</b>	0.11	0.02	0.03	0.2	0.01	0.49
<b>GRID - Variance</b>	0.01	1.84	0.97	0.01	0.84	0.03
<b>NO-GRID - Variance</b>	0.02	0	0.01	0.01	0.8	0.04

**Table 95.** The ratio between the total area of the specific damage type predicted and the total area of the field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.79	0.51	0.02	0.4	0.16
<b>NO-GRID - Mean</b>	0.02	0.57	0.03	0.03	0.27	0.09
<b>GRID - Median</b>	0.02	0	0	0.01	0	0.12
<b>NO-GRID - Median</b>	0.01	0	0	0.02	0	0.05
<b>GRID - Variance</b>	0	3.98	2.47	0	2.77	0.04
<b>NO-GRID - Variance</b>	0	4.32	0.04	0	1.38	0.01

**Table 96.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.153	0.01	0.02	0.09	0.01	0.72
<b>NO-GRID - Mean</b>	0.195	0.02	0.06	0.19	0.01	0.53

**Table 97.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<i>Ratio</i>							
<i>Total field area</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>	<i>No damage</i>
<i>GRID - Mean</i>	0.026	0	0	0.02	0	0.12	0.83
<i>NO-GRID - Mean</i>	0.024	0	0.01	0.02	0	0.07	0.88

# Appendix 3: Results - Wheat-fitted Model

The following results were calculated using the 2023 wheat and 2024 wheat data to fit the grid- and no-grid-based CNN models.

## Contents

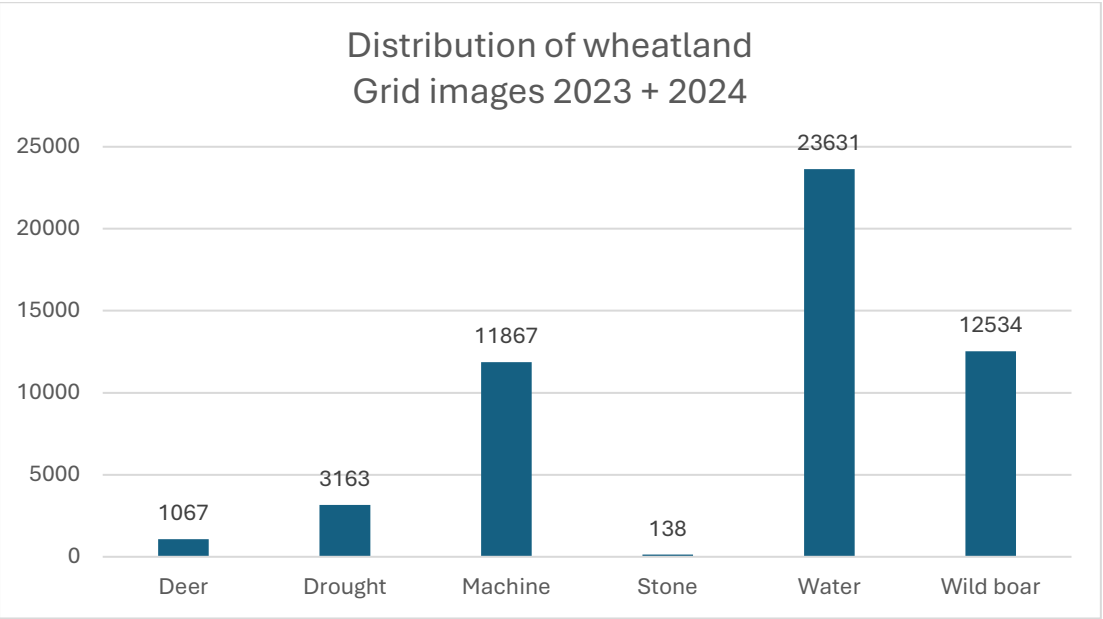
<b>1. Data Preprocessing + Model Fitting Results .....</b>	<b>110</b>
1.1 Data Distribution	110
1.2 Model Fitting Results	111
<b>2. Results 2024 Wheat - Validation polygons evaluation .....</b>	<b>111</b>
Total 2024	111
Total, 2024: GRID validation polygon evaluation .....	111
Total, 2024: NO-GRID validation polygon evaluation .....	112
Blekinge 2024	113
Blekinge, 2024: GRID validation polygon evaluation .....	113
Blekinge, 2024: NO-GRID validation polygon evaluation .....	114
Jönköping 2024	115
Jönköping, 2024: GRID validation polygon evaluation .....	115
Jönköping, 2024: NO-GRID validation polygon evaluation .....	116
Örebro 2024	117
Örebro, 2024: GRID validation polygon evaluation .....	117
Örebro, 2024: NO-GRID validation polygon evaluation .....	118
Södermanland 2024	119
Södermanland, 2024: GRID validation polygon evaluation .....	119
Södermanland, 2024: NO-GRID validation polygon evaluation .....	120
<b>3. Results 2024 - Field Prediction Evaluation .....</b>	<b>121</b>
Wheat – Wheat fitted model	121
Overlapping areas of validation polygons and created damage polygons .....	121
Field evaluation Wheat Grid / No-grid Blekinge 2024 .....	121
Blekinge 2024, Grid .....	121
Blekinge 2024. No-Grid .....	121
Overlapping areas of validation polygons and created damage polygons .....	122
Field evaluation Wheat Grid / No-grid Jönköping 2024 .....	122
Jönköping 2024, Grid .....	122
Jönköping 2024, No-Grid .....	122

Overlapping areas of validation polygons and created damage polygons .....	123
Field evaluation Wheat Grid / No-grid Örebro 2024.....	123
Örebro 2024, Grid .....	123
Örebro 2024. No-Grid .....	123
Overlapping areas of validation polygons and created damage polygons .....	124
Field evaluation Wheat Grid / No-grid Södermanland 2024 .....	124
Södermanland 2024, Grid .....	124
Södermanland 2024. No-Grid .....	124
<b>4. Post-classification Analysis – Damage Types ratios .....</b>	<b>125</b>
Wheat – Jönköping damage types ratios .....	125
Wheat - Object-based Random Forest Damage Classification.....	125
Wheat Object-based Support Vector Machine Damage Classification .....	127
Wheat Pixel-based Random Forest Damage Classification.....	128
Wheat Pixel-based Support Vector Machine Damage Classification .....	129
Wheat – Blekinge damage types ratios .....	131
Wheat - Object-based Random Forest Damage Classification.....	131
Wheat Object-based Support Vector Machine Damage Classification .....	132
Wheat Pixel-based Random Forest Damage Classification.....	133
Wheat Pixel-based Support Vector Machine Damage Classification .....	135
Wheat – Örebro damage types ratios .....	137
Wheat - Object-based Random Forest Damage Classification.....	137
Wheat Object-based Support Vector Machine Damage Classification .....	138
Wheat Pixel-based Random Forest Damage Classification.....	139
Wheat Pixel-based Support Vector Machine Damage Classification .....	140
Wheat – Södermanland damage types ratios .....	142
Wheat - Object-based Random Forest Damage Classification.....	142
Wheat Object-based Support Vector Machine Damage Classification .....	143
Wheat Pixel-based Random Forest Damage Classification.....	144
Wheat Pixel-based Support Vector Machine Damage Classification .....	145

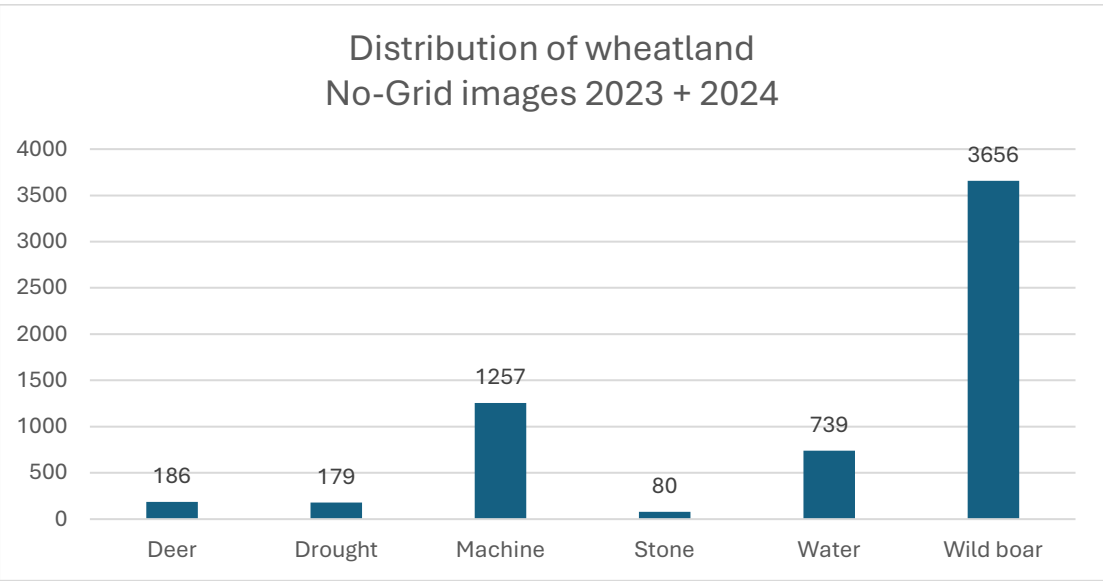
# 1. Data Preprocessing + Model Fitting Results

## 1.1 Data Distribution

Given the distribution of the wheat grid images created from 2023 and 2024 validation polygons (Figures 1 and 2), it was decided to perform 1 augmentation on machine and wild boar, and 5 augmentations on deer, drought, and stone. For the no-grid images, it was decided to perform 2 augmentations on machine, 4 augmentations on water, and 5 augmentations on deer, drought, and stone.



**Figure 17.** Distribution of the gird-based images created from the 2023 and 2024 validation polygons data of wheat.



**Figure 18.** Distribution of the no-gird-based images created from the 2023 and 2024 validation polygons data of wheat.

## 1.2 Model Fitting Results

**Table 1.** Result of the fitting of the wheat-fitted model using the grid/no-grid augmented images.

<i>Grid</i>	<i>Epo</i>	<i>Val</i>	<i>Train</i>	<i>Val</i>	<i>Train</i>	<i>No-</i>	<i>Epo</i>	<i>Val</i>	<i>Train</i>	<i>Val</i>	<i>Train</i>
	<i>chs</i>	<i>acc</i>	<i>acc</i>	<i>loss</i>	<i>loss</i>	<i>Grid</i>	<i>chs</i>	<i>acc</i>	<i>acc</i>	<i>loss</i>	<i>loss</i>
Grass	72	0.66	0.68	<b>0.91</b>	0.83	Grass	122	0.82	0.83	0.48	0.47

## 2. Results 2024 Wheat - Validation polygons evaluation

### Total 2024

#### Total, 2024: GRID validation polygon evaluation

Total instances predicted: 41908

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

#### Confusion Matrix:

<i>TRUE</i>							
<i>PRED</i>		deer	drought	machine	stone	water	Wild boar
	deer	0.77%	0.01%	0.03%	0.00%	0.44%	0.22%
	drought	0.11%	3.08%	1.38%	0.01%	3.37%	0.64%
	machine	0.12%	0.45%	17.15%	0.03%	3.83%	1.29%
	stone	0.00%	0.00%	0.00%	0.17%	0.08%	0.00%
	water	0.21%	0.70%	2.57%	0.09%	41.37%	1.43%
	wild boar	0.66%	0.50%	1.76%	0.02%	5.68%	11.83%
	total True Instances	1.87%	4.75%	22.89%	0.32%	54.77%	15.41%
		782	1990	9593	135	22951	6457

#### Overall performance:

<i>Total Accuracy</i>	<i>Total Kappa</i>	<i>Average Precision</i>	<i>Average Recall</i>	<i>Average F1score</i>
0.74	0.61	0.64	0.63	0.62

#### Class performance:

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
Deer	0.52	0.41	0.46
Drought	0.36	0.65	0.46
Machine	0.75	0.75	0.75
Stone	0.67	0.51	0.59
Water	0.89	0.76	0.82
Wild boar	0.58	0.77	0.66

## Total, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 3615

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

### Confusion Matrix:

		<b>TRUE</b>					
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	2.35%	0.00%	0.06%	0.00%	0.08%	1.16%
	<b>drought</b>	0.03%	3.35%	0.00%	0.03%	0.22%	0.25%
	<b>machine</b>	0.03%	0.03%	29.96%	0.33%	0.39%	0.25%
	<b>stone</b>	0.03%	0.00%	0.08%	1.24%	0.00%	0.72%
	<b>water</b>	0.14%	0.33%	0.33%	0.00%	17.21%	1.55%
	<b>wild boar</b>	1.63%	0.39%	0.89%	0.53%	1.52%	34.91%
<b>total True</b>		4.20%	4.09%	31.31%	2.13%	19.42%	38.84%
<b>Instances</b>		152	148	1132	77	702	1404

### Overall performance:

<i>Total</i>	<i>Total</i>	<i>Average</i>	<i>Average</i>	<i>Average</i>
<i>Accuracy</i>	<i>Kappa</i>	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
0.89	0.84	0.78	0.81	0.79

### Class performance:

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
<i>Deer</i>	0.64	0.56	0.60
<i>Drought</i>	0.86	0.82	0.84
<i>Machine</i>	0.97	0.96	0.96
<i>Stone</i>	0.60	0.58	0.59
<i>Water</i>	0.88	0.89	0.88
<i>Wild boar</i>	0.88	0.90	0.89



# Blekinge 2024

## Blekinge, 2024: GRID validation polygon evaluation

Total instances predicted: 14475

Number of fields evaluated: 40

### Confusion Matrix:

	deer	drought	machine	stone	water	Wild boar
deer	0.08%	0.02%	0.01%	0.00%	0.37%	0.16%
drought	0.00%	6.49%	1.18%	0.01%	4.06%	0.63%
machine	0.03%	0.99%	13.78%	0.02%	5.36%	0.90%
stone	0.00%	0.00%	0.00%	0.08%	0.06%	0.01%
water	0.01%	0.68%	1.42%	0.06%	45.76%	1.16%
wild boar	0.16%	0.92%	1.05%	0.01%	7.08%	7.47%
total True	0.28%	9.09%	17.43%	0.19%	62.69%	10.32%
Instances	41	1316	2523	27	9074	1494

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.74	0.02	0.58	0.05

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.13	0.03	0.29	0.02	0.18	0
Drought	0.52	0.12	0.71	0.11	0.60	0.06
Machine	0.65	0.10	0.79	0.05	0.72	0.06
Stone	0.57	0.23	0.44	0.10	0.50	0.05
Water	0.93	0.13	0.73	0.05	0.82	0.04
Wild boar	0.45	0.11	0.72	0.06	0.55	0.08

Blekinge, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 14475

Number of fields evaluated: 40

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	0.38%	0.00%	0.00%	0.00%	0.19%	0.85%
	drought	0.00%	8.68%	0.00%	0.00%	0.38%	0.00%
	machine	0.03%	0.00%	31.79%	0.19%	0.57%	0.09%
	stone	0.00%	0.00%	0.09%	0.75%	0.00%	0.47%
	water	0.00%	0.47%	0.09%	0.00%	26.32%	1.13%
	wild boar	0.47%	0.85%	1.05%	0.85%	2.26%	22.62%
total True		0.85%	10%	33.02%	1.79%	29.72%	24.62%
Instances		9	106	350	19	315	261

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.90	0.01	0.86	0.03

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.27	0.17	0.44	0.18	0.33	0.02
Drought	0.96	0.09	0.87	0.06	0.91	0.01
Machine	0.97	0.01	0.96	0	0.97	0
Stone	0.57	0.25	0.42	0.15	0.48	0.03
Water	0.94	0.04	0.89	0.02	0.91	0.01
Wild boar	0.80	0.18	0.90	0.02	0.85	0.02

## Jönköping 2024

### Jönköping, 2024: GRID validation polygon evaluation

Total instances predicted: 8458

Number of fields evaluated: 46

#### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.28%	0.01%	0.05%	0.02%	0.22%	0.27%
	drought	0.00%	0.70%	1.96%	0.00%	1.36%	0.50%
	machine	0.00%	0.11%	20.15%	0.11%	2.59%	1.74%
	stone	0.00%	0.00%	0.00%	0.41%	0.05%	0.00%
	water	0.08%	0.95%	5.34%	0.26%	36.66%	2.94%
	wild boar	0.02%	0.15%	3.07%	0.07%	3.90%	16.01%
total True		0.39%	1.92%	30.57%	0.87%	44.79%	21.46%
Instances		33	162	2586	74	3788	1815

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.74	0.04	0.61	0.03

#### Class performance:

	Precision		Recall		F1score	
	Precision	Variance	Recall	Variance	F1score	Variance
Deer	0.33	0.09	0.73	0.04	0.45	0.02
Drought	0.15	0.05	0.36	0.03	0.22	0.04
Machine	0.82	0.13	0.66	0.06	0.73	0.04
Stone	0.90	0.22	0.47	0.13	0.62	0.05
Water	0.79	0.16	0.82	0.05	0.81	0.06
Wild boar	0.69	0.15	0.75	0.06	0.72	0.05

Jönköping, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 1049

Number of fields evaluated: 46

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	0.48%	0.00%	0.19%	0.00%	0.00%	1.14%
	drought	0.00%	1.24%	0.00%	0.10%	0.19%	0.48%
	machine	0.00%	0.10%	32.41%	0.95%	0.67%	0.76%
	stone	0.10%	0.00%	0.19%	2.76%	0.00%	1.81%
	water	0.00%	0.38%	1.05%	0.00%	9.63%	2.10%
	wild boar	0.57%	0.38%	1.91%	0.86%	1.24%	38.32%
total True		1.14%	2.10%	35.75%	4.67%	11.73%	44.61%
Instances		12	22	375	49	123	468

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.85	0.04	0.77	0.05

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.26	0.10	0.42	0.17	0.32	0
Drought	0.62	0.24	0.59	0.12	0.60	0.02
Machine	0.93	0.07	0.91	0.05	0.92	0.02
Stone	0.57	0.22	0.59	0.14	0.58	0.05
Water	0.73	0.16	0.82	0.06	0.77	0.02
Wild boar	0.89	0.17	0.86	0.01	0.87	0.01

# Örebro 2024

## Örebro, 2024: GRID validation polygon evaluation

Total instances predicted: 14756

Number of fields evaluated: 40

### Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	1.74%	0.01%	0.03%	0.00%	0.45%	0.18%
	drought	0.20%	1.99%	1.48%	0.01%	2.72%	0.53%
	machine	0.22%	0.25%	22.11%	0.00%	2.49%	1.59%
	stone	0.00%	0.00%	0.00%	0.01%	0.09%	0.00%
	water	0.46%	0.77%	2.38%	0.01%	38.40%	0.91%
	wild boar	1.19%	0.41%	2.10%	0.01%	3.53%	13.70%
	total True	3.81%	3.42%	28.11%	0.04%	47.70%	16.92%
Instances		562	505	4148	6	7039	2496

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.78	0.01	0.68	0.04

### Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.72	0.17	0.46	0.04	0.56	0.05
Drought	0.29	0.07	0.58	0.02	0.38	0.02
Machine	0.83	0.06	0.79	0.02	0.81	0.02
Stone	0.13	0.16	0.33	0.17	0.18	0.06
Water	0.89	0.18	0.81	0.07	0.85	0.06
Wild boar	0.65	0.15	0.81	0.06	0.72	0.08

Örebro, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 1204

Number of fields evaluated: 40

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	5.23%	0.00%	0.00%	0.00%	0.08%	1.25%
	drought	0.08%	1.25%	0.00%	0.00%	0.00%	0.17%
	machine	0.08%	0.00%	30.48%	0.00%	0.08%	0.00%
	stone	0.00%	0.00%	0.00%	0.17%	0.00%	0.17%
	water	0.25%	0.25%	0.00%	0.00%	12.29%	1.16%
	wild boar	2.82%	0.08%	0.08%	0.08%	0.25%	43.69%
	total True	8.47%	1.58%	30.56%	0.25%	12.71%	46.43%
Instances		102	19	368	3	153	559

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.93	0.01	0.90	0.03

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.80	0.18	0.62	0.16	0.70	0.08
Drought	0.83	0.17	0.79	0.04	0.81	0.02
Machine	0.99	0	1.00	0	1.00	0
Stone	0.50	0.25	0.67	0.22	0.57	0
Water	0.88	0.10	0.97	0.01	0.92	0.01
Wild boar	0.93	0.18	0.94	0.01	0.94	0.01

## Södermanland 2024

### Södermanland, 2024: GRID validation polygon evaluation

Total instances predicted: 4219

Number of fields evaluated: 14

#### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.71%	0.02%	0.05%	0.00%	1.04%	0.47%
	drought	0.38%	0.02%	0.52%	0.02%	7.25%	1.33%
	machine	0.26%	0.00%	5.36%	0.00%	5.71%	0.66%
	stone	0.00%	0.00%	0.00%	0.50%	0.14%	0.02%
	water	0.33%	0.05%	1.66%	0.14%	46.15%	1.11%
	wild boar	1.78%	0.07%	0.38%	0.00%	11.99%	11.85%
total True		3.46%	0.17%	7.96%	0.66%	72.29%	15.45%
Instances		146	7	336	28	3050	652

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.65	0.01	0.40	0.02

#### Class performance:

	Precision		Recall		F1score	
	Precision	Variance	Recall	Variance	F1score	Variance
Deer	0.31	0.06	0.21	0.02	0.25	0.02
Drought	0	0	0.14	0	0	0
Machine	0.45	0.15	0.67	0.07	0.54	0.06
Stone	0.75	0.23	0.75	0.01	0.75	0
Water	0.93	0.11	0.64	0.03	0.76	0.02
Wild boar	0.45	0.09	0.77	0.05	0.57	0.08

Södermanland, 2024: NO-GRID validation polygon evaluation

Total instances predicted: 302

Number of fields evaluated: 14

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	4.30%	0.00%	0.00%	0.00%	0.00%	1.99%
	drought	0.00%	0.33%	0.00%	0.00%	0.66%	0.66%
	machine	0.00%	0.00%	12.91%	0.00%	0.00%	0.00%
	stone	0.00%	0.00%	0.00%	1.99%	0.00%	0.00%
	water	0.66%	0.00%	0.00%	0.00%	31.13%	2.65%
	wild boar	4.64%	0.00%	0.00%	0.00%	4.97%	33.11%
	total True	9.60%	0.33%	12.91%	1.99%	36.75%	38.41%
Instances		29	1	39	6	111	116

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.84	0.01	0.76	0.03

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.68	0.14	0.45	0.01	0.54	0.01
Drought	0.20	0.16	1.00	0	0.33	0
Machine	1.00	0	1.00	0	1.00	0
Stone	1.00	0	1.00	0	1.00	0
Water	0.88	0.04	0.89	0.02	0.90	0.02
Wild boar	0.78	0.12	0.86	0.02	0.82	0.03



### 3. Results 2024 - Field Prediction Evaluation

#### Wheat – Wheat fitted model

##### Overlapping areas of validation polygons and created damage polygons

<b>Blekinge Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
<i>Deer</i>	76	76	76	76	64	68	61	62
<i>Drought</i>	2670	2239	1802	661	890	798	361	94
<i>Machine</i>	1988	2004	1807	1718	1149	1190	828	777
<i>Stone</i>	23	22	25	24	19	18	18	17
<i>Water</i>	18968	19644	17528	17170	5750	6158	4161	4041
<i>Wild boar</i>	3461	3476	3398	3389	2499	2542	1759	1740

#### Field evaluation Wheat Grid / No-grid Blekinge 2024

##### *Blekinge 2024, Grid*

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
<i>Object RF</i>	0.70	0.48	0.49	0.40	0.50	0.45	0.72	0.41
<i>Object SVM</i>	0.70	0.47	0.49	0.39	0.49	0.44	0.72	0.41
<i>Pixel RF</i>	0.70	0.48	0.50	0.40	0.50	0.45	0.73	0.43
<i>Pixel SVM</i>	0.70	0.44	0.49	0.35	0.46	0.40	0.73	0.45

##### *Blekinge 2024. No-Grid*

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
<i>Object RF</i>	0.30	0.09	0.03	0.32	0.22	0.26	0.06	0.14
<i>Object SVM</i>	0.39	0.19	0.00	0.27	0.26	0.26	0.29	0.32
<i>Pixel RF</i>	0.36	0.17	0.09	0.35	0.29	0.31	0.19	0.30
<i>Pixel SVM</i>	0.28	0.08	0.07	0.34	0.22	0.27	0.17	0.34

## Overlapping areas of validation polygons and created damage polygons

<i>Jönköping</i> <i>Area (m<sup>2</sup>)</i>	<i>Grid</i> <i>Object</i> <i>RF</i>	<i>Grid</i> <i>Object</i> <i>SVM</i>	<i>Grid</i> <i>Pixel</i> <i>RF</i>	<i>Grid</i> <i>Pixel</i> <i>SVM</i>	<i>No-Grid</i> <i>Object</i> <i>RF</i>	<i>No-Grid</i> <i>Object</i> <i>SVM</i>	<i>No-Grid</i> <i>Pixel</i> <i>RF</i>	<i>No-Grid</i> <i>Pixel</i> <i>SVM</i>
<i>Deer</i>	2	2	2	3	2	2	1	2
<i>Drought</i>	399	345	382	339	103	78	84	47
<i>Machine</i>	2652	2626	2633	2596	1735	1762	1279	1233
<i>Stone</i>	26	26	27	24	20	18	18	11
<i>Water</i>	10900	10667	11391	10609	3943	4190	3384	3113
<i>Wild boar</i>	2914	2917	2889	2886	2331	2396	1443	1628

## Field evaluation Wheat Grid / No-grid Jönköping 2024

### *Jönköping 2024, Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.75	0.56	0.42	0.47	0.44	0.63	0.80	0.70
<i>Object</i> <i>SVM</i>	0.75	0.56	0.41	0.46	0.43	0.62	0.80	0.70
<i>Pixel</i> <i>RF</i>	0.76	0.57	0.41	0.47	0.44	0.62	0.80	0.70
<i>Pixel</i> <i>SVM</i>	0.75	0.56	0.40	0.46	0.43	0.62	0.81	0.70

### *Jönköping 2024, No-Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.28	-0.08	0.14	0.15	0.15	0.34	0.35	0.35
<i>Object</i> <i>SVM</i>	0.50	0.18	0.23	0.22	0.23	0.46	0.43	0.44
<i>Pixel</i> <i>RF</i>	0.56	0.34	0.34	0.31	0.32	0.40	0.93	0.56
<i>Pixel</i> <i>SVM</i>	0.56	0.33	0.36	0.29	0.32	0.42	0.90	0.57

## Overlapping areas of validation polygons and created damage polygons

<b>Örebro Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	1124	1117	705	899	506	509	107	180
Drought	1457	1438	1189	1155	713	695	302	212
Machine	3435	3401	2979	2893	2144	2131	1706	1630
Stone	4	4	4	4	3	2	2	2
Water	17059	17102	11609	12385	5541	5866	2884	2941
Wild boar	4427	4420	4186	3873	3152	3195	1555	1411

## Field evaluation Wheat Grid / No-grid Örebro 2024

### Örebro 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.78	0.60	0.58	0.52	0.57	0.54	0.84	0.60
Object SVM	0.77	0.59	0.59	0.52	0.56	0.54	0.84	0.60
Pixel RF	0.77	0.61	0.60	0.52	0.57	0.55	0.85	0.66
Pixel SVM	0.78	0.61	0.60	0.53	0.56	0.54	0.86	0.63

### Örebro 2024. No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.55	0.31	0.03	0.27	0.28	0.27	0.73	0.47
Object SVM	0.42	0.15	0.04	0.22	0.23	0.23	0.53	0.35
Pixel RF	0.55	0.37	0.10	0.35	0.32	0.34	0.90	0.40
Pixel SVM	0.54	0.36	0.11	0.36	0.33	0.35	0.92	0.36

## Overlapping areas of validation polygons and created damage polygons

<i>Södermanland Area (m<sup>2</sup>)</i>	<i>Grid Object RF</i>	<i>Grid Object SVM</i>	<i>Grid Pixel RF</i>	<i>Grid Pixel SVM</i>	<i>No-Grid Object RF</i>	<i>No-Grid Object SVM</i>	<i>No-Grid Pixel RF</i>	<i>No-Grid Pixel SVM</i>
<i>Deer</i>	242	244	250	236	101	106	63	51
<i>Drought</i>	14	14	14	14	12	8	0	0
<i>Machine</i>	392	393	383	374	236	243	175	175
<i>Stone</i>	41	41	41	41	40	40	39	39
<i>Water</i>	11237	11560	10633	9968	6372	5488	2393	2438
<i>Wild boar</i>	1162	1164	1153	1145	786	802	538	552

## Field evaluation Wheat Grid / No-grid Södermanland 2024

### *Södermanland 2024, Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.39	0.11	0.20	0.32	0.38	0.35	0.67	0.22
<i>Object SVM</i>	0.40	0.11	0.20	0.35	0.38	0.37	0.67	0.22
<i>Pixel RF</i>	0.40	0.12	0.21	0.31	0.38	0.34	0.67	0.23
<i>Pixel SVM</i>	0.41	0.12	0.22	0.31	0.38	0.35	0.67	0.24

### *Södermanland 2024. No-Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.75	0.21	-0.01	0.21	0.22	0.22	0.50	0.23
<i>Object SVM</i>	0.70	0.31	0.00	0.33	0.33	0.33	0.83	0.29
<i>Pixel RF</i>	0.30	0.08	0.01	0.29	0.23	0.26	0.96	0.22
<i>Pixel SVM</i>	0.43	0.15	0.02	0.29	0.26	0.28	0.94	0.25

## 4. Post-classification Analysis – Damage Types ratios

### Wheat – Jönköping damage types ratios

#### Wheat - Object-based Random Forest Damage Classification

**Table 2.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	846239m <sup>2</sup>	9616m <sup>2</sup>	10443m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 3.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.27</b>	0.27	0.01

**Table 4.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.31	0.01	0.14	0.28	0.28	0.33
<b>NO-GRID - Mean</b>	0.38	0.01	0.07	0.11	0.36	0.43
<b>GRID - Median</b>	0.23	0.01	0.12	0.26	0	0.29
<b>NO-GRID - Median</b>	0.37	0	0.03	0.05	0	0.43
<b>GRID - Variance</b>	0.37	0	0.01	0.04	1.99	0.05
<b>NO-GRID - Variance</b>	0.03	0	0.01	0.02	2.38	0.03

**Table 5.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.1	0.11	0.03	0.15	0.86	0.08
<b>NO-GRID - Mean</b>	0.07	0.26	0.1	0.02	2.05	0.08
<b>GRID - Median</b>	0.06	0	0.03	0.06	0	0.06
<b>NO-GRID - Median</b>	0.06	0	0.01	0.01	0	0.08
<b>GRID - Variance</b>	0.05	0.88	0	0.51	5.17	0
<b>NO-GRID - Variance</b>	0	2.09	0.64	0	10.79	0.01

**Table 6.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.29	0.01	0.13	0.31	0	0.26
<b>NO-GRID - Mean</b>	0.38	0.01	0.05	0.17	0	0.4

**Table 7.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.079	0	0.04	0.08	0	0.07	0.73
<b>NO-GRID - Mean</b>	0.078	0	0.01	0.03	0	0.08	0.79

## Wheat Object-based Support Vector Machine Damage Classification

**Table 8.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	822171m <sup>2</sup>	9343m <sup>2</sup>	10361m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 9.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.26</b>	0.25	0.02

**Table 10.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.13	0.28	0.16	0.33
<b>NO-GRID - Mean</b>	0.39	0.07	0.06	0.15	0.47	0.43
<b>GRID - Median</b>	0.23	0.01	0.12	0.26	0	0.28
<b>NO-GRID - Median</b>	0.37	0	0.02	0.06	0	0.43
<b>GRID - Variance</b>	0.02	0	0.01	0.04	0.72	0.05
<b>NO-GRID - Variance</b>	0.04	0.38	0.01	0.1	3	0.03

**Table 11.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.13	0.03	0.07	1	0.07
<b>NO-GRID - Mean</b>	0.07	0.57	0.01	0.05	1.85	0.09
<b>GRID - Median</b>	0.05	0	0.03	0.06	0	0.06
<b>NO-GRID - Median</b>	0.06	0	0	0.01	0	0.07
<b>GRID - Variance</b>	0.01	0.94	0	0	5.97	0
<b>NO-GRID - Variance</b>	0	3.54	0	0.04	8.36	0.01

**Table 12.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<i>Ratio</i>						
<i>Predicted damages</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>GRID - Mean</i>	0.31	0.01	0.13	0.31	0	0.24
<i>NO-GRID - Mean</i>	0.347	0.01	0.05	0.18	0	0.42

**Table 13.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<i>Ratio</i>							
<i>Total field area</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>	<i>No damage</i>
<i>GRID - Mean</i>	0.082	0	0.03	0.08	0	0.06	0.74
<i>NO-GRID - Mean</i>	0.071	0	0.01	0.04	0	0.09	0.79

## Wheat Pixel-based Random Forest Damage Classification

**Table 14.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<i>Total Field Predicted</i>	<i>Damage Area Total</i>	<i>Damage Area Mean</i>	<i>Damage Area Standard Deviation</i>	<i>Field Area Total</i>	<i>Field Area Mean</i>	<i>Field Area Standard Deviation</i>
88	468370m <sup>2</sup>	5322m <sup>2</sup>	5187m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 15.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<i>Ratio Damage vs Field Area Mean</i>	<i>Ratio Damage vs Field Area Median</i>	<i>Ratio Damage vs Field Area Variance</i>
0.17	0.16	0

**Table 16.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<i>Ratio</i>						
<i>Predicted damage</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>GRID - Mean</i>	0.23	0.01	0.16	0.26	0.03	0.34
<i>NO-GRID - Mean</i>	0.51	0.01	0.08	0.12	0	0.28
<i>GRID - Median</i>	0.22	0.01	0.14	0.23	0	0.3
<i>NO-GRID - Median</i>	0.52	0.01	0.03	0.06	0	0.26
<i>GRID - Variance</i>	0.02	0	0.01	0.04	0.07	0.06
<i>NO-GRID - Variance</i>	0.04	0	0.02	0.02	0	0.02



**Table 17.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.37	0.03	0.04	1.01	0.05
<b>NO-GRID - Mean</b>	0.05	0.64	0.01	0.17	1.21	0.03
<b>GRID - Median</b>	0.03	0	0.02	0.03	0	0.04
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.02
<b>GRID - Variance</b>	0	2.56	0	0	5.17	0
<b>NO-GRID - Variance</b>	0	3.98	0	0.92	6.23	0

**Table 18.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.273	0.01	0.17	0.27	0	0.27
<b>NO-GRID - Mean</b>	0.506	0.01	0.08	0.14	0	0.26

**Table 19.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.041	0	0.03	0.04	0	0.04	0.85
<b>NO-GRID - Mean</b>	0.047	0	0.01	0.01	0	0.02	0.91

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 20.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	492891m <sup>2</sup>	5601m <sup>2</sup>	7099m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 21.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0.01

**Table 22.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.24	0.01	0.16	0.25	0.03	0.34
<b>NO-GRID - Mean</b>	0.54	0.01	0.07	0.1	0.12	0.28
<b>GRID - Median</b>	0.24	0.01	0.15	0.21	0	0.31
<b>NO-GRID - Median</b>	0.54	0	0.03	0.04	0	0.28
<b>GRID - Variance</b>	0.02	0	0.01	0.04	0.07	0.06
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.02	0.57	0.02

**Table 23.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.75	0.02	0.03	0.98	0.05
<b>NO-GRID - Mean</b>	0.05	0.93	0.03	0.33	1.61	0.03
<b>GRID - Median</b>	0.03	0	0.02	0.03	0	0.04
<b>NO-GRID - Median</b>	0.05	0	0	0	0	0.02
<b>GRID - Variance</b>	0	5.25	0	0	5.23	0
<b>NO-GRID - Variance</b>	0	5.35	0.05	2.35	8.01	0

**Table 24.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.289	0.01	0.17	0.25	0	0.28
<b>NO-GRID - Mean</b>	0.554	0.01	0.07	0.11	0	0.26

**Table 25.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.046	0	0.03	0.04	0	0.04	0.84
<b>NO-GRID - Mean</b>	0.055	0	0.01	0.01	0	0.03	0.9

## Wheat – Blekinge damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 26.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	274024m <sup>2</sup>	4725m <sup>2</sup>	3905m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 27.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0.01

**Table 28.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.14	0.35	0.23	0.23
<b>NO-GRID - Mean</b>	0.48	0.01	0.03	0.16	0.16	0.31
<b>GRID - Median</b>	0.21	0.01	0.08	0.36	0	0.18
<b>NO-GRID - Median</b>	0.44	0.01	0.01	0.11	0	0.29
<b>GRID - Variance</b>	0.03	0	0.02	0.04	1.75	0.03
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.03	1.39	0.03

**Table 29.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.04	0.02	0.17	1.47	0.03
<b>NO-GRID - Mean</b>	0.06	0.34	0.06	0.02	2.87	0.03
<b>GRID - Median</b>	0.03	0	0.01	0.04	0	0.02
<b>NO-GRID - Median</b>	0.04	0	0	0.01	1.92	0.03
<b>GRID - Variance</b>	0	0.08	0	0.81	7.83	0
<b>NO-GRID - Variance</b>	0	2.56	0.19	0	10.18	0

**Table 30.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.267	0.01	0.13	0.4	0	0.19
<b>NO-GRID - Mean</b>	0.454	0.01	0.04	0.2	0	0.29

**Table 31.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.035	0	0.02	0.05	0	0.02	0.87
<b>NO-GRID - Mean</b>	0.046	0	0	0.02	0	0.03	0.9

## Wheat Object-based Support Vector Machine Damage Classification

**Table 32.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	340475m <sup>2</sup>	5870m <sup>2</sup>	5472m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 33.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.18</b>	0.15	0.01

**Table 34.** The ratio between the total area of the specific *damage* type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.13	0.36	0.51	0.24
<b>NO-GRID - Mean</b>	0.5	0.01	0.04	0.18	0.45	0.28
<b>GRID - Median</b>	0.22	0.01	0.09	0.35	0	0.19
<b>NO-GRID - Median</b>	0.47	0.01	0.01	0.12	0	0.27
<b>GRID - Variance</b>	0.03	0	0.02	0.04	3.44	0.03
<b>NO-GRID - Variance</b>	0.05	0	0.01	0.04	3.16	0.03

**Table 35.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0	0.02	0.06	1.82	0.04
<b>NO-GRID - Mean</b>	0.07	0.34	0.88	0.27	2.48	0.03
<b>GRID - Median</b>	0.03	0	0.01	0.05	0	0.03
<b>NO-GRID - Median</b>	0.05	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	0	0	0	9.4	0
<b>NO-GRID - Variance</b>	0	1.77	5.32	1.97	9.58	0

**Table 36.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.271	0.01	0.13	0.41	0	0.17
<b>NO-GRID - Mean</b>	0.423	0.01	0.05	0.22	0	0.3

**Table 37.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.044	0	0.02	0.07	0	0.03	0.84
<b>NO-GRID - Mean</b>	0.054	0	0.01	0.03	0	0.04	0.87

## Wheat Pixel-based Random Forest Damage Classification

**Table 38.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	149803m <sup>2</sup>	2583m <sup>2</sup>	2231m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 39.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.08</b>	0.08	0

**Table 40.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.28	0.01	0.14	0.31	0	0.26
<b>NO-GRID - Mean</b>	0.68	0.01	0.02	0.14	0.01	0.14
<b>GRID - Median</b>	0.23	0.01	0.11	0.32	0	0.21
<b>NO-GRID - Median</b>	0.7	0	0	0.09	0.01	0.13
<b>GRID - Variance</b>	0.04	0	0.02	0.03	0	0.03
<b>NO-GRID - Variance</b>	0.03	0	0	0.02	0	0.01

**Table 41.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.38	0.01	0.02	1.14	0.02
<b>NO-GRID - Mean</b>	0.03	1.64	1.04	0.1	0.36	0.15
<b>GRID - Median</b>	0.01	0	0.01	0.02	0	0.02
<b>NO-GRID - Median</b>	0.03	0	0	0	0	0.01
<b>GRID - Variance</b>	0	2.71	0	0	4.09	0
<b>NO-GRID - Variance</b>	0	8.72	5.05	0.48	1.99	1.13

**Table 42.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.273	0.02	0.16	0.35	0	0.21
<b>NO-GRID - Mean</b>	0.635	0.01	0.03	0.16	0.01	0.16

**Table 43.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0.01	0.02	0	0.01	0.93
<b>NO-GRID - Mean</b>	0.029	0	0	0.01	0	0.01	0.95

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 44.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	114222m <sup>2</sup>	1969m <sup>2</sup>	1787m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 45.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.07</b>	0.06	0

**Table 46.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.29	0.02	0.1	0.3	0	0.29
<b>NO-GRID - Mean</b>	0.71	0.01	0	0.14	0.01	0.13
<b>GRID - Median</b>	0.25	0.01	0.05	0.3	0	0.23
<b>NO-GRID - Median</b>	0.75	0	0	0.08	0.01	0.12
<b>GRID - Variance</b>	0.04	0	0.01	0.04	0	0.04
<b>NO-GRID - Variance</b>	0.04	0	0	0.02	0	0.01

**Table 47.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.48	0	0.02	1.17	0.02
<b>NO-GRID - Mean</b>	0.03	1.39	0.7	0.29	0.59	0.11
<b>GRID - Median</b>	0.01	0	0	0.01	0	0.01
<b>NO-GRID - Median</b>	0.02	0	0	0	0	0
<b>GRID - Variance</b>	0	3.2	0	0	5.18	0
<b>NO-GRID - Variance</b>	0	7.42	3.82	1.6	3.22	0.61

**Table 48.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.298	0.02	0.09	0.35	0	0.24
<b>NO-GRID - Mean</b>	0.669	0.01	0.01	0.16	0.01	0.14

**Table 49.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.016	0	0.01	0.02	0	0.01	0.95
<b>NO-GRID - Mean</b>	0.025	0	0	0.01	0	0.01	0.96



## Wheat – Örebro damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 50.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	574950m <sup>2</sup>	6388m <sup>2</sup>	4703m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 51.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.25</b>	0.2	0.05

**Table 52.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.22	0.05	0.15	0.44	0.09	0.17
<b>NO-GRID - Mean</b>	0.4	0.01	0.08	0.24	0.73	0.26
<b>GRID - Median</b>	0.19	0.01	0.11	0.44	0	0.12
<b>NO-GRID - Median</b>	0.37	0.01	0.01	0.19	0	0.25
<b>GRID - Variance</b>	0.02	0.1	0.02	0.05	0.65	0.02
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.05	3.82	0.02

**Table 53.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.31	0.04	0.09	0.58	0.04
<b>NO-GRID - Mean</b>	0.07	0.14	0.09	0.04	3.04	0.04
<b>GRID - Median</b>	0.03	0	0.02	0.08	0	0.02
<b>NO-GRID - Median</b>	0.05	0	0	0.02	2.54	0.04
<b>GRID - Variance</b>	0	1.54	0	0.01	3.99	0
<b>NO-GRID - Variance</b>	0	1.16	0.46	0	9.09	0

**Table 54.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.285	0.02	0.13	0.42	0	0.14
<b>NO-GRID - Mean</b>	0.427	0.01	0.07	0.24	0	0.26

**Table 55.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.057	0	0.03	0.08	0	0.03	0.8
<b>NO-GRID - Mean</b>	0.064	0	0.01	0.04	0	0.04	0.85

## Wheat Object-based Support Vector Machine Damage Classification

**Table 56.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	528531m <sup>2</sup>	5873m <sup>2</sup>	4405m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 57.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.22</b>	0.18	0.05

**Table 58.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.22	0.18	0.15	0.45	0.1	0.16
<b>NO-GRID - Mean</b>	0.39	0.01	0.08	0.25	0.96	0.28
<b>GRID - Median</b>	0.19	0.01	0.1	0.46	0	0.1
<b>NO-GRID - Median</b>	0.35	0.01	0.01	0.22	0	0.23
<b>GRID - Variance</b>	0.02	1.32	0.02	0.05	0.83	0.02
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.04	6.45	0.02

**Table 59.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.44	0.03	0.09	0.88	0.03
<b>NO-GRID - Mean</b>	0.06	0.22	0.22	0.04	2.16	0.04
<b>GRID - Median</b>	0.03	0	0.02	0.08	0	0.02
<b>NO-GRID - Median</b>	0.04	0	0	0.02	1.69	0.03
<b>GRID - Variance</b>	0	2.91	0	0.01	5.74	0
<b>NO-GRID - Variance</b>	0	1.75	1.3	0	6.06	0

**Table 60.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.282	0.02	0.13	0.43	0	0.13
<b>NO-GRID - Mean</b>	0.425	0.02	0.06	0.24	0	0.25

**Table 61.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.052	0	0.02	0.08	0	0.02	0.82
<b>NO-GRID - Mean</b>	0.061	0	0.01	0.03	0	0.04	0.86

## Wheat Pixel-based Random Forest Damage Classification

**Table 62.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	215817m <sup>2</sup>	2398m <sup>2</sup>	1912m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 63.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.1</b>	0.08	0.01

**Table 64.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.22	0.01	0.19	0.42	0.09	0.16
<b>NO-GRID - Mean</b>	0.35	0.02	0.1	0.33	0.44	0.2
<b>GRID - Median</b>	0.18	0	0.14	0.39	0	0.1
<b>NO-GRID - Median</b>	0.35	0.01	0.03	0.31	0	0.15
<b>GRID - Variance</b>	0.02	0	0.02	0.05	0.75	0.02
<b>NO-GRID - Variance</b>	0.03	0	0.02	0.04	3.4	0.04

**Table 65.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	1.34	0.02	0.03	0.74	0.01
<b>NO-GRID - Mean</b>	0.02	0.5	0.55	0.02	2.66	0.01
<b>GRID - Median</b>	0.01	0	0.01	0.03	0	0.01
<b>NO-GRID - Median</b>	0.01	0	0	0.01	1.68	0.01
<b>GRID - Variance</b>	0	8.03	0	0	4.54	0
<b>NO-GRID - Variance</b>	0	3.27	2.96	0	8.84	0

**Table 66.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.272	0.02	0.2	0.38	0	0.13
<b>NO-GRID - Mean</b>	0.339	0.02	0.12	0.31	0	0.2

**Table 67.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.021	0	0.01	0.03	0	0.01	0.92
<b>NO-GRID - Mean</b>	0.017	0	0.01	0.02	0	0.01	0.95

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 68.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	226896m <sup>2</sup>	2521m <sup>2</sup>	2308m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 69.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.1</b>	0.08	0.01

**Table 70.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.21	0.15	0.21	0.4	0.1	0.17
<b>NO-GRID - Mean</b>	0.36	0.01	0.08	0.31	0.47	0.23
<b>GRID - Median</b>	0.17	0	0.18	0.38	0	0.11
<b>NO-GRID - Median</b>	0.36	0.01	0.02	0.28	0	0.17
<b>GRID - Variance</b>	0.02	0.89	0.02	0.04	0.81	0.02
<b>NO-GRID - Variance</b>	0.03	0	0.02	0.04	3.83	0.04

**Table 71.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	1.25	0.02	0.03	0.64	0.01
<b>NO-GRID - Mean</b>	0.02	1.24	0.59	0.02	2.68	0.01
<b>GRID - Median</b>	0.01	0	0.01	0.03	0	0.01
<b>NO-GRID - Median</b>	0.01	0	0	0.01	1.55	0.01
<b>GRID - Variance</b>	0	6.89	0	0	3.64	0
<b>NO-GRID - Variance</b>	0	7.6	3.29	0	9.16	0

**Table 72.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.265	0.02	0.22	0.36	0	0.13
<b>NO-GRID - Mean</b>	0.377	0.01	0.1	0.28	0	0.22

**Table 73.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.021	0	0.02	0.03	0	0.01	0.92
<b>NO-GRID - Mean</b>	0.02	0	0.01	0.01	0	0.01	0.95

## Wheat – Södermanland damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 74.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	535732m <sup>2</sup>	15307m <sup>2</sup>	21235m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 75.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.23	0.02

**Table 76.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.03	0.17	0.25	0.47	0.3
<b>NO-GRID - Mean</b>	0.37	0.01	0.05	0.08	0.16	0.49
<b>GRID - Median</b>	0.23	0.02	0.15	0.2	0	0.19
<b>NO-GRID - Median</b>	0.36	0	0.01	0.03	0	0.44
<b>GRID - Variance</b>	0.04	0	0.01	0.04	3.66	0.05
<b>NO-GRID - Variance</b>	0.05	0	0.02	0.01	0.9	0.06

**Table 77.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.25	0.05	0.06	0.97	0.08
<b>NO-GRID - Mean</b>	0.07	0.43	0.18	0.27	0.07	0.11
<b>GRID - Median</b>	0.05	0.01	0.03	0.05	0	0.06
<b>NO-GRID - Median</b>	0.05	0	0	0.01	0	0.06
<b>GRID - Variance</b>	0.01	2.04	0	0	4.13	0.01
<b>NO-GRID - Variance</b>	0.01	3.12	0.91	2.3	0.16	0.01

**Table 78.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.301	0.03	0.19	0.27	0	0.21
<b>NO-GRID - Mean</b>	0.317	0.01	0.04	0.15	0	0.49

**Table 79.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.073	0.01	0.05	0.07	0	0.05	0.76
<b>NO-GRID - Mean</b>	0.058	0	0.01	0.03	0	0.09	0.82

## Wheat Object-based Support Vector Machine Damage Classification

**Table 80.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	514574m <sup>2</sup>	14702m <sup>2</sup>	21318m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 81.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.26</b>	0.21	0.02

**Table 82.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.03	0.17	0.25	0.72	0.29
<b>NO-GRID - Mean</b>	0.4	0.01	0.02	0.14	0	0.43
<b>GRID - Median</b>	0.24	0.02	0.15	0.2	0	0.19
<b>NO-GRID - Median</b>	0.35	0	0	0.03	0	0.42
<b>GRID - Variance</b>	0.04	0	0.01	0.04	5.7	0.05
<b>NO-GRID - Variance</b>	0.06	0	0	0.04	0	0.06

**Table 83.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.01	0.04	0.05	1.09	0.07
<b>NO-GRID - Mean</b>	0.08	0.89	0.33	0.27	0.93	0.08
<b>GRID - Median</b>	0.04	0	0.03	0.04	0	0.05
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.06
<b>GRID - Variance</b>	0.01	0	0	0	4.7	0
<b>NO-GRID - Variance</b>	0.01	5.84	1.84	2.07	7	0.01

**Table 84.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.312	0.03	0.18	0.27	0	0.2
<b>NO-GRID - Mean</b>	0.348	0	0.03	0.22	0	0.4

**Table 85.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.073	0.01	0.04	0.06	0	0.05	0.77
<b>NO-GRID - Mean</b>	0.062	0	0.01	0.04	0	0.07	0.82

## Wheat Pixel-based Random Forest Damage Classification

**Table 86.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	319425m <sup>2</sup>	9126m <sup>2</sup>	13113m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 87.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.15	0.01

**Table 88.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.24	0.02	0.19	0.21	0	0.33
<b>NO-GRID - Mean</b>	0.57	0.01	0.02	0.16	0.02	0.22
<b>GRID - Median</b>	0.2	0.01	0.16	0.16	0	0.23
<b>NO-GRID - Median</b>	0.63	0	0	0.04	0.01	0.19
<b>GRID - Variance</b>	0.04	0	0.01	0.03	0	0.06
<b>NO-GRID - Variance</b>	0.05	0	0	0.05	0	0.02



**Table 89.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0	0.03	0.03	1.47	0.05
<b>NO-GRID - Mean</b>	0.04	1.47	0.5	0.49	0.08	0.02
<b>GRID - Median</b>	0.03	0	0.02	0.02	0	0.04
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.01
<b>GRID - Variance</b>	0	0	0	0	8.01	0
<b>NO-GRID - Variance</b>	0	8.46	2.74	3.18	0.23	0

**Table 90.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.272	0.02	0.21	0.25	0	0.24
<b>NO-GRID - Mean</b>	0.547	0	0.01	0.23	0.01	0.19

**Table 91.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.04	0	0.03	0.04	0	0.04	0.85
<b>NO-GRID - Mean</b>	0.042	0	0	0.02	0	0.01	0.92

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 92.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	360601m <sup>2</sup>	10303m <sup>2</sup>	17534m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 93.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0

**Table 94.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.24	0.03	0.2	0.21	0	0.32
<b>NO-GRID - Mean</b>	0.56	0.01	0.02	0.13	0.01	0.27
<b>GRID - Median</b>	0.19	0.01	0.19	0.17	0	0.22
<b>NO-GRID - Median</b>	0.63	0	0.01	0.03	0.01	0.22
<b>GRID - Variance</b>	0.03	0	0.01	0.03	0	0.06
<b>NO-GRID - Variance</b>	0.04	0	0	0.03	0	0.03

**Table 95.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.23	0.03	0.03	1.41	0.05
<b>NO-GRID - Mean</b>	0.05	0.82	0.09	0.48	0.08	0.02
<b>GRID - Median</b>	0.03	0	0.02	0.02	0	0.03
<b>NO-GRID - Median</b>	0.03	0	0	0	0	0.02
<b>GRID - Variance</b>	0	1.85	0	0	8.09	0
<b>NO-GRID - Variance</b>	0	3.59	0.13	3.88	0.22	0

**Table 96.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.281	0.03	0.22	0.25	0	0.22
<b>NO-GRID - Mean</b>	0.506	0.01	0.02	0.23	0.01	0.23

**Table 97.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.046	0	0.04	0.04	0	0.04	0.84
<b>NO-GRID - Mean</b>	0.047	0	0	0.02	0	0.02	0.91

# Appendix 4: Results - Fulldata-fitted Model

The following results were calculated using the 2023 wheat and grass and 2024 wheat and grass data to fit the grid- and no-grid-based CNN models.

## Contents

### 1. Results 2024 - Validation polygons evaluation .....151

Total 2024	151
Total, 2024, Grassland .....	151
Total, 2024 Grassland: GRID validation polygon evaluation .....	151
Total, 2024 Grassland: NO-GRID validation polygon evaluation .....	152
Total, 2024, wheat.....	153
Total, 2024 wheat: GRID validation polygon evaluation.....	153
Total, 2024 Wheat: NO-GRID validation polygon evaluation .....	154
Blekinge, 2024	155
Blekinge 2024, Grassland.....	155
Blekinge, 2024, grass: GRID validation polygon evaluation .....	155
Blekinge, 2024, grass: NO-GRID validation polygon evaluation .....	156
Blekinge 2024, Wheat .....	157
Blekinge, 2024, wheat: GRID validation polygon evaluation .....	157
Blekinge, 2024, wheat: NO-GRID validation polygon evaluation.....	158
Jönköping, 2024	159
Jönköping 2024, Grassland.....	159
Jönköping, 2024, grass: GRID validation polygon evaluation .....	159
Jönköping, 2024, grass: NO-GRID validation polygon evaluation.....	160
Jönköping 2024, Wheat .....	161
Jönköping, 2024, wheat: GRID validation polygon evaluation.....	161
Jönköping, 2024, wheat: NO-GRID validation polygon evaluation.....	162
Örebro, 2024	163
Örebro, 2024, Grassland .....	163
Örebro, 2024, grass: GRID validation polygon evaluation.....	163
Örebro, 2024, grass: NO-GRID validation polygon evaluation .....	164
Örebro, 2024, Wheat.....	165
Örebro, 2024, wheat: GRID validation polygon evaluation .....	165
Örebro, 2024, wheat: NO-GRID validation polygon evaluation .....	166

Södermanland, 2024	167
Södermanland, 2024, grassland .....	167
Södermanland, 2024, grass: GRID validation polygon evaluation.....	167
Södermanland, 2024, grass: NO-GRID validation polygon evaluation .....	168
Södermanland, 2024, wheat.....	169
Södermanland, 2024, wheat: GRID validation polygon evaluation .....	169
Södermanland, 2024, wheat: NO-GRID validation polygon evaluation .....	170
<b>2. Results 2024 - Field Prediction Evaluation.....</b>	<b>171</b>
Wheat – fulldata fitted model	171
Overlapping areas of validation polygons and created damage polygons .....	171
Field evaluation Wheat Grid / No-grid Blekinge 2024 .....	171
Blekinge 2024, Grid .....	171
Blekinge 2024, No-Grid.....	171
Overlapping areas of validation polygons and created damage polygons .....	172
Field evaluation Wheat Grid / No-grid Jönköping 2024 .....	172
Jönköping 2024, Grid .....	172
Jönköping 2024, No-Grid.....	172
Overlapping areas of validation polygons and created damage polygons .....	173
Field evaluation Wheat Grid / No-grid Örebro 2024.....	173
Örebro 2024, Grid .....	173
Örebro 2024, No-Grid .....	173
Overlapping areas of validation polygons and created damage polygons .....	174
Field evaluation Wheat Grid / No-grid Södermanland 2024 .....	174
Södermanland 2024, Grid .....	174
Södermanland 2024, No-Grid .....	174
Grass - fulldata fitted model	175
Overlapping areas of validation polygons and created damage polygons .....	175
Field evaluation Grass Grid / No-grid Blekinge 2024 .....	175
Blekinge 2024, Grid .....	175
Blekinge 2024, No-Grid.....	175
Overlapping areas of validation polygons and created damage polygons .....	176
Field evaluation Grass Grid / No-grid Jönköping 2024 .....	176
Jönköping 2024, Grid .....	176
Jönköping 2024, No-Grid.....	176
Overlapping areas of validation polygons and created damage polygons .....	177

Field evaluation Grass Grid / No-grid Örebro 2024.....	177
Örebro 2024, Grid .....	177
Örebro 2024, No-Grid .....	177
Overlapping areas of validation polygons and created damage polygons .....	178
Field evaluation Grass Grid / No-grid Södermanland 2024 .....	178
Södermanland 2024, Grid .....	178
Södermanland 2024, No-Grid .....	178
<b>3. Post-classification Analysis – Damage Types ratios .....</b>	<b>179</b>
Wheat – Jönköping damage types ratios .....	179
Wheat - Object-based Random Forest Damage Classification .....	179
Wheat Object-based Support Vector Machine Damage Classification .....	180
Wheat Pixel-based Random Forest Damage Classification .....	181
Wheat Pixel-based Support Vector Machine Damage Classification .....	183
Grass – Jönköping damage types ratios .....	185
Grass - Object-based Random Forest Damage Classification .....	185
Grass - Object-based Support Vector Machine Damage Classification .....	186
Grass – Pixel-based Random Forest Damage Classification .....	188
Grass - Pixel-based Support Vector Machine Damage Classification .....	189
Wheat – Blekinge damage types ratios .....	190
Wheat - Object-based Random Forest Damage Classification .....	190
Wheat Object-based Support Vector Machine Damage Classification .....	192
Wheat Pixel-based Random Forest Damage Classification .....	193
Wheat Pixel-based Support Vector Machine Damage Classification .....	195
Grass – Blekinge damage types ratios .....	196
Grass - Object-based Random Forest Damage Classification .....	196
Grass - Object-based Support Vector Machine Damage Classification .....	197
Grass – Pixel-based Random Forest Damage Classification .....	199
Grass - Pixel-based Support Vector Machine Damage Classification .....	200
Wheat – Örebro damage types ratios .....	201
Wheat - Object-based Random Forest Damage Classification .....	201
Wheat Object-based Support Vector Machine Damage Classification .....	203
Wheat Pixel-based Random Forest Damage Classification .....	204
Wheat Pixel-based Support Vector Machine Damage Classification .....	205
Grass – Örebro damage types ratios .....	207
Grass - Object-based Random Forest Damage Classification .....	207

Grass - Object-based Support Vector Machine Damage Classification .....	208
Grass – Pixel-based Random Forest Damage Classification .....	209
Grass - Pixel-based Support Vector Machine Damage Classification .....	211
Wheat – Södermanland damage types ratios	213
Wheat - Object-based Random Forest Damage Classification.....	213
Wheat Object-based Support Vector Machine Damage Classification .....	214
Wheat Pixel-based Random Forest Damage Classification.....	215
Wheat Pixel-based Support Vector Machine Damage Classification .....	216
Grass – Södermanland damage types ratios	218
Grass - Object-based Random Forest Damage Classification.....	218
Grass - Object-based Support Vector Machine Damage Classification .....	219
Grass – Pixel-based Random Forest Damage Classification .....	220
Grass - Pixel-based Support Vector Machine Damage Classification .....	221

# 1. Results 2024 - Validation polygons evaluation

## Total 2024

### Total, 2024, Grassland

Total, 2024 Grassland: GRID validation polygon evaluation

Total instances predicted: 32455

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

#### Confusion Matrix:

TRUE		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.62%	0.04%	0.07%	0.02%	0.35%	0.09%
	drought	0.09%	2.06%	0.84%	0.21%	3.26%	0.63%
	machine	0.04%	0.13%	7.75%	0.15%	2.95%	0.78%
	stone	0.02%	0.03%	0.33%	1.63%	0.47%	0.46%
	water	0.22%	1.52%	5.35%	0.62%	56.15%	2.25%
	wild boar	0.07%	0.29%	1.57%	0.53%	4.36%	4.02%
total True		1.07%	4.08%	15.91%	3.17%	67.53%	8.23%
Instances		347	1325	5165	1029	21918	2671

#### Overall performance:

Total Accuracy	Total Kappa	Average Precision	Average Recall	Average F1score
0.72	0.47	0.57	0.54	0.55

#### Class performance:

	Precision	Recall	F1score
Deer	0.52	0.58	0.55
Drought	0.29	0.50	0.37
Machine	0.66	0.49	0.56
Stone	0.56	0.49	0.53
Water	0.85	0.83	0.84
Wild boar	0.37	0.49	0.42

*Total, 2024 Grassland: NO-GRID validation polygon evaluation*

Total instances predicted: 2657

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

**Confusion Matrix:**

		<b>TRUE</b>					
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	2.94%	0.08%	0.56%	0.11%	0.00%	1.69%
	<b>drought</b>	0.00%	2.22%	0.26%	0.11%	0.19%	0.60%
	<b>machine</b>	0.15%	0.23%	24.05%	0.04%	1.35%	3.58%
	<b>stone</b>	0.08%	0.19%	0.72%	12.19%	0.15%	6.25%
	<b>water</b>	0.11%	0.68%	1.69%	0.15%	10.84%	3.69%
	<b>wild boar</b>	0.19%	0.19%	2.63%	2.52%	0.90%	18.67%
<b>total True</b>		3.46%	3.58%	29.92%	15.13%	13.44%	34.47%
<b>Instances</b>		92	95	795	402	357	916

**Overall performance:**

<i>Total</i>	<i>Total</i>	<i>Average</i>	<i>Average</i>	<i>Average</i>
<i>Accuracy</i>	<i>Kappa</i>	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
0.71	0.62	0.74	0.70	0.69

**Class performance:**

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
<i>Deer</i>	0.55	0.85	0.66
<i>Drought</i>	0.66	0.62	0.64
<i>Machine</i>	0.82	0.80	0.81
<i>Stone</i>	0.62	0.81	0.70
<i>Water</i>	0.63	0.81	0.71
<i>Wild boar</i>	0.74	0.54	0.63



## Total, 2024, wheat

Total, 2024 wheat: GRID validation polygon evaluation

Total instances predicted: 41908

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.61%	0.01%	0.02%	0.00%	0.38%	0.19%
	drought	0.14%	2.78%	1.53%	0.02%	4.43%	0.73%
	machine	0.12%	0.55%	16.69%	0.03%	4.78%	1.35%
	stone	0.00%	0.00%	0.01%	0.11%	0.16%	0.01%
	water	0.24%	0.79%	2.61%	0.11%	37.41%	1.51%
	wild boar	0.75%	0.61%	2.03%	0.05%	7.61%	11.63%
total True		1.87%	4.75%	22.89%	0.32%	54.77%	15.41%
Instances		782	1990	9593	135	22951	6457

### Overall performance:

Total Accuracy	Total Kappa	Average Precision	Average Recall	Average F1score
0.69	0.54	0.57	0.54	0.54

### Class performance:

	Precision	Recall	F1score
Deer	0.50	0.33	0.39
Drought	0.29	0.59	0.39
Machine	0.71	0.73	0.72
Stone	0.38	0.34	0.36
Water	0.88	0.68	0.77
Wild boar	0.51	0.75	0.61

*Total, 2024 Wheat: NO-GRID validation polygon evaluation*

Total instances predicted:

Study areas evaluated: Blekinge, Jönköping, Örebro, Södermanland

**Confusion Matrix:**

<i>TRUE</i>							
<i>PRED</i>		deer	drought	machine	stone	water	Wild boar
	deer	1.74%	0.00%	0.03%	0.00%	0.11%	0.94%
	drought	0.03%	2.79%	0.06%	0.00%	0.41%	0.39%
	machine	0.06%	0.08%	28.99%	0.03%	0.53%	0.50%
	stone	0.08%	0.00%	0.00%	0.64%	0.00%	0.41%
	water	0.30%	0.66%	0.47%	0.06%	16.57%	1.99%
	wild boar	1.99%	0.55%	1.77%	1.41%	1.80%	34.61%
<b>total True</b>		4.20%	4.09%	31.31%	2.13%	19.42%	38.84%
<b>Instances</b>		152	148	1132	77	702	1404

**Overall performance:**

<i>Total</i>	<i>Total</i>	<i>Average</i>	<i>Average</i>	<i>Average</i>
<i>Accuracy</i>	<i>Kappa</i>	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
0.85	0.79	0.68	0.76	0.71

**Class performance:**

	<i>Precision</i>	<i>Recall</i>	<i>F1score</i>
<i>Deer</i>	0.62	0.41	0.50
<i>Drought</i>	0.76	0.68	0.72
<i>Machine</i>	0.96	0.93	0.94
<i>Stone</i>	0.56	0.30	0.39
<i>Water</i>	0.83	0.85	0.84
<i>Wild boar</i>	0.82	0.89	0.85

Blekinge, 2024

Blekinge 2024, Grassland

Blekinge, 2024, grass: GRID validation polygon evaluation

Total instances predicted: 3253

Number of fields evaluated: 38

Confusion Matrix:

TRUE							
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.00%	0.18%	0.12%	0.03%	0.25%	0.31%
	drought	0.00%	4.83%	1.38%	0.83%	0.92%	0.83%
	machine	0.00%	0.25%	19.21%	0.43%	1.72%	1.97%
	stone	0.00%	0.03%	0.77%	7.84%	0.43%	1.29%
	water	0.00%	3.35%	5.41%	1.97%	20.10%	7.01%
	wild boar	0.00%	0.92%	2.67%	2.03%	3.50%	9.41%
total True		0.00%	9.56%	29.57%	13.13%	26.93%	20.81%
Instances		0	311	962	427	876	677

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.61	0.04	0.50	0.02

Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0	0	/	/	/	/
Drought	0.55	0.09	0.50	0.04	0.53	0.03
Machine	0.65	0.18	0.72	0.07	0.76	0.06
Stone	0.76	0.19	0.60	0.09	0.67	0.04
Water	0.53	0.13	0.75	0.05	0.62	0.04
Wild boar	0.51	0.18	0.45	0.07	0.48	0.05

*Blekinge, 2024, grass: NO-GRID validation polygon evaluation*

Total instances predicted: 393

Number of fields evaluated: 38

**Confusion Matrix:**

		<b>TRUE</b>					
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	0.00%	0.00%	0.00%	0.00%	0.00%	0.25%
	<b>drought</b>	0.00%	1.78%	0.00%	0.51%	0.00%	1.53%
	<b>machine</b>	0.00%	0.76%	15.78%	0.25%	0.25%	1.02%
	<b>stone</b>	0.00%	0.25%	0.25%	32.32%	0.00%	3.31%
	<b>water</b>	0.00%	1.53%	1.78%	0.00%	4.07%	6.62%
	<b>wild boar</b>	0.00%	0.51%	0.51%	6.87%	0.25%	19.59%
<b>total True</b>		0.00%	4.83%	18.32%	39.95%	4.58%	32.32%
<b>Instances</b>		0	19	72	157	18	127

**Overall performance:**

<i>Total</i>	<i>Variance</i>	<i>Total</i>	<i>Variance</i>
<i>Accuracy</i>	<i>Accuracy</i>	<i>Kappa</i>	<i>Kappa</i>
0.74	0.04	0.63	0.07

**Class performance:**

		<i>Variance</i>		<i>Variance</i>		<i>Variance</i>
	<i>Precision</i>	<i>Precision</i>	<i>Recall</i>	<i>Recall</i>	<i>F1score</i>	<i>F1score</i>
<i>Deer</i>	0	0	/	/	/	/
<i>Drought</i>	0.47	0.22	0.37	0.14	0.41	0.06
<i>Machine</i>	0.87	0.15	0.86	0.06	0.87	0.01
<i>Stone</i>	0.89	0.16	0.81	0.04	0.85	0.02
<i>Water</i>	0.29	0.20	0.89	0.05	0.44	0.04
<i>Wild boar</i>	0.71	0.16	0.61	0.11	0.65	0.04

## Blekinge 2024, Wheat

*Blekinge, 2024, wheat: GRID validation polygon evaluation*

Total instances predicted: 14475

Number of fields evaluated: 40

### Confusion Matrix:

<i>TRUE</i>							
		deer	drought	machine	stone	water	Wild boar
<i>PRED</i>	deer	0.06%	0.02%	0.00%	0.00%	0.24%	0.11%
	drought	0.01%	6.04%	1.28%	0.02%	4.77%	0.69%
	machine	0.03%	1.22%	13.48%	0.03%	6.72%	0.98%
	stone	0.00%	0.00%	0.01%	0.05%	0.15%	0.00%
	water	0.01%	0.75%	1.47%	0.07%	41.89%	1.27%
	wild boar	0.18%	1.07%	1.19%	0.02%	8.91%	7.27%
total True		0.28%	9.09%	17.43%	0.19%	62.69%	10.32%
Instances		41	1316	2523	27	9074	1494

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.69	0.03	0.52	0.04

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.13	0.05	0.20	0.01	0.16	0
Drought	0.47	0.11	0.66	0.11	0.55	0.07
Machine	0.60	0.09	0.77	0.04	0.68	0.06
Stone	0.23	0.14	0.26	0.05	0.25	0.05
Water	0.92	0.14	0.67	0.05	0.77	0.04
Wild boar	0.39	0.10	0.70	0.06	0.50	0.07

# *Blekinge, 2024, wheat: NO-GRID validation polygon evaluation*

Total instances predicted: 1060

Number of fields evaluated: 40

## **Confusion Matrix:**

<b>TRUE</b>							
<b>PRED</b>		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
	<b>deer</b>	0.19%	0.00%	0.00%	0.00%	0.19%	0.47%
	<b>drought</b>	0.00%	7.74%	0.09%	0.00%	0.47%	0.09%
	<b>machine</b>	0.00%	0.00%	30.57%	0.00%	0.85%	0.28%
	<b>stone</b>	0.00%	0.00%	0.00%	0.28%	0.00%	0.19%
	<b>water</b>	0.00%	0.94%	0.09%	0.09%	25.28%	1.70%
	<b>wild boar</b>	0.66%	1.32%	2.26%	1.42%	2.92%	21.89%
	<b>total True</b>	0.85%	10.00%	33.02%	1.79%	29.72%	24.62%
<b>Instances</b>		9	106	350	19	315	261

## **Overall performance:**

<i>Total</i>	<i>Variance</i>	<i>Total</i>	<i>Variance</i>
<i>Accuracy</i>	<i>Accuracy</i>	<i>Kappa</i>	<i>Kappa</i>
0.86	0.02	0.81	0.04

## **Class performance:**

		<i>Variance</i>		<i>Variance</i>		<i>Variance</i>
	<i>Precision</i>	<i>Precision</i>	<i>Recall</i>	<i>Recall</i>	<i>F1score</i>	<i>F1score</i>
<i>Deer</i>	0.22	0.17	0.22	0.17	0.22	0.11
<i>Drought</i>	0.92	0.10	0.77	0.10	0.84	0.03
<i>Machine</i>	0.96	0.01	0.93	0.02	0.94	0.01
<i>Stone</i>	0.60	0.25	0.16	0.10	0.25	0.03
<i>Water</i>	0.90	0.07	0.85	0.03	0.87	0.02
<i>Wild boar</i>	0.72	0.18	0.89	0.02	0.79	0.03

## Jönköping, 2024

### Jönköping 2024, Grassland

*Jönköping, 2024, grass: GRID validation polygon evaluation*

Total instances predicted: 5147

Number of fields evaluated: 42

#### Confusion Matrix:

<b>TRUE</b>							
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	0.00%	0.04%	0.19%	0.10%	0.47%	0.25%
	<b>drought</b>	0.00%	4.53%	2.39%	0.60%	2.66%	2.53%
	<b>machine</b>	0.00%	0.54%	15.12%	0.56%	3.65%	2.51%
	<b>stone</b>	0.00%	0.17%	0.89%	2.91%	0.45%	0.85%
	<b>water</b>	0.00%	2.00%	9.87%	1.07%	24.31%	3.05%
	<b>wild boar</b>	0.00%	0.60%	3.67%	0.93%	4.27%	8.80%
<b>total True</b>		0.00%	7.89%	32.14%	6.18%	35.81%	17.99%
<b>Instances</b>		0	406	1654	318	1843	926

#### Overall performance:

<i>Total</i>	<i>Variance</i>	<i>Total</i>	<i>Variance</i>
<i>Accuracy</i>	<i>Accuracy</i>	<i>Kappa</i>	<i>Kappa</i>
0.56	0.06	0.40	0.02

#### Class performance:

		<i>Variance</i>		<i>Variance</i>		<i>Variance</i>
	<i>Precision</i>	<i>Precision</i>	<i>Recall</i>	<i>Recall</i>	<i>F1score</i>	<i>F1score</i>
<i>Deer</i>	0	0	/	/	/	/
<i>Drought</i>	0.36	0.11	0.57	0.12	0.44	0.07
<i>Machine</i>	0.68	0.16	0.47	0.05	0.55	0.04
<i>Stone</i>	0.55	0.19	0.47	0.07	0.51	0.05
<i>Water</i>	0.60	0.12	0.68	0.03	0.64	0.04
<i>Wild boar</i>	0.48	0.13	0.49	0.04	0.49	0.06

### Jönköping, 2024, grass: NO-GRID validation polygon evaluation

Total instances predicted: 1050

Number of fields evaluated: 42

#### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.00%	0.19%	1.14%	0.29%	0.00%	3.52%
	drought	0.00%	3.62%	0.29%	0.10%	0.10%	0.86%
	machine	0.00%	0.29%	25.52%	0.00%	0.67%	5.81%
	stone	0.00%	0.29%	0.86%	11.62%	0.19%	8.19%
	water	0.00%	0.57%	1.81%	0.29%	6.00%	2.67%
	wild boar	0.00%	0.10%	2.86%	1.05%	0.76%	20.38%
total True		0.00%	5.05%	32.48%	13.33%	7.71%	41.43%
Instances		0	53	341	140	81	435

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.67	0.03	0.56	0.07

#### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0	0	/	/	/	/
Drought	0.73	0.23	0.72	0.12	0.72	0.05
Machine	0.79	0.10	0.79	0.03	0.79	0.02
Stone	0.55	0.17	0.87	0.02	0.67	0.05
Water	0.53	0.17	0.78	0.12	0.63	0.02
Wild boar*	0.81	0.21	0.49	0.08	0.61	0.05

\* High variance for the wild boar precision between the different fields, some fields have a precision of zero while others have 100%. 27 out of the 42 fields did not have any wild boar damage present.



## Jönköping 2024, Wheat

*Jönköping, 2024, wheat: GRID validation polygon evaluation*

Total instances predicted: 8458

Number of fields evaluated: 46

### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.27%	0.02%	0.02%	0.01%	0.26%	0.38%
	drought	0.00%	0.38%	2.16%	0.02%	3.16%	0.83%
	machine	0.00%	0.15%	19.47%	0.09%	3.12%	1.77%
	stone	0.00%	0.00%	0.05%	0.31%	0.09%	0.01%
	water	0.09%	1.19%	5.26%	0.30%	32.64%	3.01%
	wild boar	0.02%	0.17%	3.61%	0.14%	5.51%	15.45%
total True		0.39%	1.92%	30.57%	0.87%	44.79%	21.46%
Instances		33	162	2586	74	3788	1815

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.69	0.04	0.54	0.04

### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.28	0.07	0.70	0.03	0.40	0.02
Drought	0.06	0.03	0.20	0.03	0.09	0.02
Machine	0.79	0.11	0.64	0.06	0.71	0.04
Stone	0.67	0.21	0.35	0.11	0.46	0.08
Water	0.77	0.16	0.73	0.07	0.75	0.06
Wild boar	0.62	0.15	0.72	0.06	0.67	0.04

*Jönköping, 2024, wheat: NO-GRID validation polygon evaluation*

Total instances predicted: 1049

Number of fields evaluated: 46

**Confusion Matrix:**

<i>TRUE</i>							
		deer	drought	machine	stone	water	Wild boar
<i>PRED</i>	deer	0.19%	0.00%	0.10%	0.00%	0.10%	0.86%
	drought	0.00%	0.67%	0.00%	0.00%	0.38%	0.86%
	machine	0.10%	0.29%	32.22%	0.10%	0.76%	0.86%
	stone	0.10%	0.00%	0.00%	1.14%	0.00%	0.95%
	water	0.10%	0.67%	1.43%	0.10%	9.06%	2.76%
	wild boar	0.67%	0.48%	2.00%	3.34%	1.43%	38.32%
total True		1.14%	2.10%	35.75%	4.67%	11.73%	44.61%
Instances		12	22	375	49	123	468

**Overall performance:**

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.82	0.05	0.72	0.08

**Class performance:**

	<i>Variance</i>		<i>Variance</i>		<i>Variance</i>	
	Precision	Precision	Recall	Recall	F1score	F1score
Deer	0.15	0.11	0.17	0.03	0.16	0
Drought	0.35	0.16	0.32	0.05	0.33	0.01
Machine	0.94	0.07	0.90	0.06	0.92	0.02
Stone	0.52	0.21	0.24	0.08	0.33	0.03
Water	0.64	0.18	0.77	0.11	0.70	0.05
Wild boar	0.83	0.16	0.86	0.02	0.84	0.03

Örebro, 2024

Örebro, 2024, Grassland

Örebro, 2024, grass: GRID validation polygon evaluation

Total instances predicted: 11423

Number of fields evaluated: 43

Confusion Matrix:

TRUE							
		deer	drought	machine	stone	water	Wild boar
PRED	deer	1.67%	0.05%	0.05%	0.01%	0.49%	0.02%
	drought	0.21%	1.63%	0.40%	0.04%	3.45%	0.12%
	machine	0.10%	0.01%	6.59%	0.05%	3.74%	0.25%
	stone	0.04%	0.00%	0.20%	0.53%	0.50%	0.15%
	water	0.40%	0.97%	4.27%	0.45%	66.32%	1.46%
	wild boar	0.15%	0.17%	0.98%	0.25%	2.99%	1.30%
total True		2.57%	2.83%	12.50%	1.31%	77.49%	3.29%
Instances		294	323	1428	150	8852	376

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.78	0.04	0.46	0.04

Class performance:

	Variance		Variance		Variance	
	Precision	Precision	Recall	Recall	F1score	F1score
Deer	0.73	0.17	0.65	0.08	0.38	0.03
Drought	0.28	0.06	0.58	0.04	0.38	0.04
Machine	0.61	0.12	0.53	0.06	0.57	0.05
Stone	0.37	0.15	0.40	0.10	0.38	0.07
Water	0.90	0.15	0.86	0.03	0.88	0.05
Wild boar	0.22	0.08	0.39	0.07	0.28	0.04

Örebro, 2024, grass: NO-GRID validation polygon evaluation

Total instances predicted: 680

Number of fields evaluated: 43

**Confusion Matrix:**

		<b>TRUE</b>					
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	8.82%	0.00%	0.29%	0.00%	0.00%	0.88%
	<b>drought</b>	0.00%	0.88%	0.15%	0.00%	0.15%	0.00%
	<b>machine</b>	0.44%	0.00%	27.79%	0.00%	3.53%	2.65%
	<b>stone</b>	0.00%	0.00%	0.29%	4.71%	0.15%	4.71%
	<b>water</b>	0.15%	0.29%	1.62%	0.15%	15.59%	1.32%
	<b>wild boar</b>	0.15%	0.15%	3.09%	2.06%	1.76%	18.24%
<b>total True</b>		9.56%	1.32%	33.24%	6.91%	21.18%	27.79%
<b>Instances</b>		65	9	226	47	144	189

**Overall performance:**

<i>Total</i>	<i>Variance</i>	<i>Total</i>	<i>Variance</i>
<i>Accuracy</i>	<i>Accuracy</i>	<i>Kappa</i>	<i>Kappa</i>
0.76	0.04	0.68	0.08

**Class performance:**

		<i>Variance</i>		<i>Variance</i>		<i>Variance</i>
	<i>Precision</i>	<i>Precision</i>	<i>Recall</i>	<i>Recall</i>	<i>F1score</i>	<i>F1score</i>
<i>Deer</i>	0.88	0.22	0.92	0.02	0.90	0.03
<i>Drought</i>	0.75	0.20	0.67	0.07	0.71	0.04
<i>Machine</i>	0.81	0.13	0.84	0.17	0.82	0.02
<i>Stone</i>	0.48	0.18	0.68	0.12	0.56	0.07
<i>Water</i>	0.82	0.12	0.74	0.08	0.77	0.04
<i>Wild boar</i>	0.72	0.20	0.66	0.06	0.69	0.03

Örebro, 2024, Wheat

Örebro, 2024, wheat: GRID validation polygon evaluation

Total instances predicted: 14756

Number of fields evaluated: 40

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	1.40%	0.01%	0.03%	0.00%	0.42%	0.14%
	drought	0.27%	1.75%	1.65%	0.00%	3.42%	0.56%
	machine	0.24%	0.29%	21.63%	0.00%	3.31%	1.63%
	stone	0.00%	0.01%	0.01%	0.00%	0.20%	0.01%
	water	0.54%	0.81%	2.44%	0.01%	34.91%	0.93%
	wild boar	1.36%	0.56%	2.34%	0.03%	5.44%	13.66%
	total True	3.81%	3.42%	28.11%	0.04%	47.70%	16.92%
Instances		562	505	4148	6	7039	2496

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.73	0.02	0.61	0.04

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.70	0.12	0.37	0.02	0.48	0.06
Drought	0.23	0.05	0.51	0.04	0.32	0.03
Machine	0.80	0.07	0.77	0.02	0.78	0.03
Stone	0	0	0	0	/	/
Water	0.88	0.18	0.73	0.06	0.80	0.04
Wild boar	0.58	0.14	0.81	0.04	0.68	0.08

Örebro, 2024, wheat: NO-GRID validation polygon evaluation

Total instances predicted: 1204

Number of fields evaluated: 40

**Confusion Matrix:**

<i>TRUE</i>							
<i>PRED</i>		deer	drought	machine	stone	water	Wild boar
	deer	4.40%	0.00%	0.00%	0.00%	0.00%	1.41%
	drought	0.00%	1.00%	0.00%	0.00%	0.42%	0.25%
	machine	0.08%	0.00%	29.07%	0.00%	0.08%	0.50%
	stone	0.08%	0.00%	0.00%	0.17%	0.00%	0.25%
	water	0.42%	0.50%	0.00%	0.00%	12.04%	1.25%
	wild boar	3.49%	0.08%	1.50%	0.08%	0.17%	42.77%
	total True	8.47%	1.58%	30.56%	0.25%	12.71%	46.43%
Instances		102	19	368	3	153	559

**Overall performance:**

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.89	0.02	0.84	0.04

**Class performance:**

	<i>Precision</i>		<i>Recall</i>		<i>F1score</i>	
		Variance		Variance		Variance
Deer	0.76	0.18	0.52	0.13	0.62	0.04
Drought	0.60	0.20	0.63	0.13	0.62	0.03
Machine	0.98	0	0.95	0.01	0.96	0
Stone	0.33	0.22	0.67	0.22	0.44	0
Water	0.85	0.10	0.95	0.04	0.90	0.02
Wild boar	0.89	0.21	0.92	0.05	0.91	0.02

## Södermanland, 2024

### Södermanland, 2024, grassland

*Södermanland, 2024, grass: GRID validation polygon evaluation*

Total instances predicted: 12632

Number of fields evaluated: 45

#### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.08%	0.00%	0.02%	0.01%	0.20%	0.03%
	drought	0.05%	0.74%	0.47%	0.06%	3.93%	0.27%
	machine	0.02%	0.05%	2.84%	0.01%	2.26%	0.26%
	stone	0.02%	0.00%	0.10%	0.51%	0.46%	0.36%
	water	0.21%	1.35%	4.47%	0.25%	69.21%	1.40%
	wild boar	0.04%	0.12%	0.96%	0.24%	5.85%	3.16%
total True		0.42%	2.26%	8.87%	1.06%	81.91%	5.48%
Instances		53	285	1121	134	10347	692

#### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.77	0.05	0.34	0.03

#### Class performance:

	Precision	Variance Precision	Recall	Variance Recall	F1score	Variance F1score
Deer	0.23	0.16	0.19	0.03	0.21	0.07
Drought	0.13	0.08	0.33	0.03	0.19	0.03
Machine	0.52	0.16	0.32	0.08	0.40	0.05
Stone	0.35	0.16	0.48	0.08	0.41	0.07
Water	0.90	0.19	0.84	0.04	0.87	0.08
Wild boar	0.30	0.09	0.58	0.08	0.40	0.04

*Södermanland, 2024, grass: NO-GRID validation polygon evaluation*

Total instances predicted: 534

Number of fields evaluated: 45

**Confusion Matrix:**

		<b>TRUE</b>					
		<b>deer</b>	<b>drought</b>	<b>machine</b>	<b>stone</b>	<b>water</b>	<b>Wild boar</b>
<b>PRED</b>	<b>deer</b>	3.37%	0.00%	0.19%	0.00%	0.00%	0.19%
	<b>drought</b>	0.00%	1.50%	0.56%	0.00%	0.56%	0.19%
	<b>machine</b>	0.19%	0.00%	22.47%	0.00%	0.75%	2.25%
	<b>stone</b>	0.37%	0.19%	1.31%	8.05%	0.19%	6.55%
	<b>water</b>	0.37%	0.75%	1.50%	0.00%	19.29%	6.55%
	<b>wild boar</b>	0.75%	0.19%	3.18%	2.81%	0.56%	15.17%
<b>total True</b>		5.06%	2.62%	29.21%	10.86%	21.35%	30.90%
<b>Instances</b>		27	14	156	58	114	165

**Overall performance:**

<i>Total</i>	<i>Variance</i>	<i>Total</i>	<i>Variance</i>
<i>Accuracy</i>	<i>Accuracy</i>	<i>Kappa</i>	<i>Kappa</i>
0.70	0.06	0.61	0.08

**Class performance:**

		<i>Variance</i>		<i>Variance</i>		<i>Variance</i>
	<i>Precision</i>	<i>Precision</i>	<i>Recall</i>	<i>Recall</i>	<i>F1score</i>	<i>F1score</i>
<i>Deer</i>	0.90	0.15	0.67	0.14	0.77	0.06
<i>Drought</i>	0.53	0.25	0.57	0.11	0.55	0.01
<i>Machine</i>	0.88	0.11	0.77	0.09	0.82	0.03
<i>Stone</i>	0.48	0.19	0.74	0.11	0.59	0.03
<i>Water</i>	0.68	0.17	0.90	0.04	0.77	0.05
<i>Wild boar</i>	0.67	0.18	0.49	0.13	0.57	0.04



## Södermanland, 2024, wheat

*Södermanland, 2024, wheat: GRID validation polygon evaluation*

Total instances predicted: 4219

Number of fields evaluated: 14

### Confusion Matrix:

		TRUE					
		deer	drought	machine	stone	water	Wild boar
PRED	deer	0.40%	0.00%	0.07%	0.00%	1.00%	0.28%
	drought	0.45%	0.02%	0.64%	0.09%	9.32%	1.30%
	machine	0.24%	0.00%	4.88%	0.02%	6.61%	0.76%
	stone	0.00%	0.00%	0.00%	0.31%	0.12%	0.00%
	water	0.33%	0.05%	1.75%	0.21%	40.32%	1.30%
	wild boar	2.04%	0.09%	0.62%	0.02%	14.93%	11.80%
total True		3.46%	0.17%	7.96%	0.66%	72.29%	15.45%
Instances		146	7	336	28	3050	652

### Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.58	0.02	0.32	0.02

### Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.23	0.05	0.12	0.01	0.15	0.01
Drought	0	0	0.14	0	0	0
Machine	0.39	0.15	0.61	0.07	0.48	0.06
Stone	0.72	0.20	0.46	0.04	0.57	0.04
Water	0.92	0.11	0.56	0.03	0.69	0.02
Wild boar	0.40	0.08	0.76	0.05	0.53	0.08

Södermanland, 2024, wheat: NO-GRID validation polygon evaluation

Total instances predicted: 241  
Number of fields evaluated: 14

Confusion Matrix:

TRUE							
PRED		deer	drought	machine	stone	water	Wild boar
	deer	1.99%	0.00%	0.00%	0.00%	0.33%	0.99%
	drought	0.33%	0.00%	0.33%	0.00%	0.33%	0.33%
	machine	0.00%	0.00%	11.92%	0.00%	0.33%	0.00%
	stone	0.33%	0.00%	0.00%	1.99%	0.00%	0.00%
	water	1.66%	0.33%	0.33%	0.00%	30.13%	3.31%
	wild boar	5.30%	0.00%	0.33%	0.00%	5.63%	33.77%
	total True	9.60%	0.33%	12.91%	1.99%	36.75%	38.41%
Instances		29	1	39	6	111	116

Overall performance:

Total	Variance	Total	Variance
Accuracy	Accuracy	Kappa	Kappa
0.80	0.02	0.70	0.04

Class performance:

	Precision		Recall		F1score	
		Variance		Variance		Variance
Deer	0.60	0.18	0.21	0.03	0.31	0.04
Drought	0	0	0	0	/	/
Machine	0.97	0.01	0.92	0.03	0.95	0.01
Stone	0.86	0.19	1	0	0.92	0
Water	0.84	0.05	0.82	0.03	0.83	0.03
Wild boar	0.75	0.14	0.88	0.12	0.81	0.03

## 2. Results 2024 - Field Prediction Evaluation

### Wheat – fulldata fitted model

#### Overlapping areas of validation polygons and created damage polygons

<b>Blekinge Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	76	76	76	76	64	68	61	62
Drought	2670	2239	1802	661	890	798	361	94
Machine	1988	2004	1807	1718	1149	1190	828	777
Stone	23	22	25	24	19	18	18	17
Water	18968	19644	17528	17170	5750	6158	4161	4041
Wild boar	3461	3476	3398	3389	2499	2542	1759	1740

### Field evaluation Wheat Grid / No-grid Blekinge 2024

#### Blekinge 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.70	0.48	0.49	0.40	0.50	0.45	0.72	0.41
Object SVM	0.70	0.47	0.49	0.39	0.49	0.44	0.72	0.41
Pixel RF	0.70	0.48	0.50	0.40	0.50	0.45	0.73	0.43
Pixel SVM	0.70	0.44	0.49	0.35	0.46	0.40	0.73	0.45

#### Blekinge 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.41	0.06	0.00	0.27	0.26	0.27	0.49	0.29
Object SVM	0.47	0.16	0.02	0.26	0.25	0.25	0.58	0.35
Pixel RF	0.41	0.17	0.05	0.26	0.28	0.27	0.83	0.31
Pixel SVM	0.41	0.18	0.07	0.27	0.29	0.28	0.74	0.32

## Overlapping areas of validation polygons and created damage polygons

<i>Jönköping</i> <i>Area (m<sup>2</sup>)</i>	<i>Grid</i> <i>Object</i> <i>RF</i>	<i>Grid</i> <i>Object</i> <i>SVM</i>	<i>Grid</i> <i>Pixel</i> <i>RF</i>	<i>Grid</i> <i>Pixel</i> <i>SVM</i>	<i>No-Grid</i> <i>Object</i> <i>RF</i>	<i>No-Grid</i> <i>Object</i> <i>SVM</i>	<i>No-Grid</i> <i>Pixel</i> <i>RF</i>	<i>No-Grid</i> <i>Pixel</i> <i>SVM</i>
<i>Deer</i>	2	2	2	3	2	2	1	2
<i>Drought</i>	399	345	384	339	103	78	84	47
<i>Machine</i>	2652	2626	2633	2596	1735	1762	1279	1233
<i>Stone</i>	26	26	27	24	20	18	18	11
<i>Water</i>	10900	10667	11391	10609	3943	4190	3384	3113
<i>Wild boar</i>	2914	2917	2889	2886	2331	2396	1443	1628

## Field evaluation Wheat Grid / No-grid Jönköping 2024

### *Jönköping 2024, Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.68	0.46	0.38	0.43	0.40	0.53	0.78	0.63
<i>Object</i> <i>SVM</i>	0.68	0.46	0.38	0.42	0.40	0.53	0.78	0.63
<i>Pixel</i> <i>RF</i>	0.68	0.46	0.38	0.42	0.40	0.52	0.78	0.62
<i>Pixel</i> <i>SVM</i>	0.68	0.46	0.39	0.43	0.41	0.52	0.78	0.63

### *Jönköping 2024, No-Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.31	0.05	0.18	0.16	0.17	0.42	0.51	0.46
<i>Object</i> <i>SVM</i>	0.61	0.39	0.31	0.30	0.31	0.55	0.83	0.66
<i>Pixel</i> <i>RF</i>	0.37	0.15	0.29	0.26	0.27	0.29	0.93	0.44
<i>Pixel</i> <i>SVM</i>	0.57	0.36	0.36	0.30	0.33	0.42	0.90	0.58

## Overlapping areas of validation polygons and created damage polygons

<b>Örebro Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
<i>Deer</i>	1124	1117	705	899	506	509	107	180
<i>Drought</i>	1457	1438	1189	1155	713	695	302	212
<i>Machine</i>	3435	3401	2979	2893	2144	2131	1706	1630
<i>Stone</i>	4	4	4	4	3	2	2	2
<i>Water</i>	17059	17102	11609	12385	5541	5866	2884	2941
<i>Wild boar</i>	4427	4420	4186	3873	3152	3195	1555	1411

## Field evaluation Wheat Grid / No-grid Örebro 2024

### Örebro 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
<i>Object RF</i>	0.71	0.51	0.54	0.48	0.53	0.50	0.83	0.51
<i>Object SVM</i>	0.70	0.50	0.54	0.48	0.52	0.50	0.83	0.51
<i>Pixel RF</i>	0.69	0.52	0.56	0.48	0.52	0.50	0.85	0.56
<i>Pixel SVM</i>	0.69	0.51	0.56	0.48	0.52	0.50	0.86	0.53

### Örebro 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
<i>Object RF</i>	0.45	0.15	0.02	0.26	0.22	0.24	0.42	0.28
<i>Object SVM</i>	0.39	0.09	0.03	0.25	0.21	0.22	0.43	0.27
<i>Pixel RF</i>	0.53	0.36	0.11	0.35	0.35	0.35	0.84	0.40
<i>Pixel SVM</i>	0.55	0.37	0.11	0.35	0.33	0.34	0.91	0.38

## Overlapping areas of validation polygons and created damage polygons

<i>Södermanland Area (m<sup>2</sup>)</i>	<i>Grid Object RF</i>	<i>Grid Object SVM</i>	<i>Grid Pixel RF</i>	<i>Grid Pixel SVM</i>	<i>No-Grid Object RF</i>	<i>No-Grid Object SVM</i>	<i>No-Grid Pixel RF</i>	<i>No-Grid Pixel SVM</i>
<i>Deer</i>	242	244	250	236	101	106	63	51
<i>Drought</i>	14	14	14	14	12	8	0	0
<i>Machine</i>	392	393	383	374	236	243	175	175
<i>Stone</i>	41	41	41	41	40	40	39	39
<i>Water</i>	11237	11560	10633	9968	6372	5488	2393	2438
<i>Wild boar</i>	1162	1164	1153	1145	786	802	538	552

## Field evaluation Wheat Grid / No-grid Södermanland 2024

### *Södermanland 2024, Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.36	0.09	0.17	0.30	0.34	0.32	0.61	0.18
<i>Object SVM</i>	0.38	0.10	0.18	0.31	0.34	0.33	0.61	0.18
<i>Pixel RF</i>	0.37	0.10	0.18	0.32	0.34	0.33	0.61	0.19
<i>Pixel SVM</i>	0.38	0.10	0.19	0.32	0.34	0.33	0.61	0.19

### *Södermanland 2024, No-Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.46	0.03	-0.03	0.20	0.33	0.25	0.43	0.11
<i>Object SVM</i>	0.69	0.27	-0.01	0.27	0.25	0.26	0.75	0.28
<i>Pixel RF</i>	0.24	0.04	0.01	0.20	0.20	0.20	0.78	0.20
<i>Pixel SVM</i>	0.39	0.13	0.01	0.23	0.24	0.24	0.83	0.24

## Grass - fulldata fitted model

### Overlapping areas of validation polygons and created damage polygons

<b>Blekinge Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	0	0	0	0	0	0	0	0
Drought	665	644	925	727	288	304	328	223
Machine	2182	2195	2191	2191	1676	1675	1279	1324
Stone	390	391	389	388	369	371	361	362
Water	2300	2200	2214	1943	1037	1093	655	524
Wild boar	1495	1495	1485	1484	1195	1219	936	902

## Field evaluation Grass Grid / No-grid Blekinge 2024

### Blekinge 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.53	0.36	0.35	0.41	0.40	0.41	0.35	0.45
Object SVM	0.53	0.36	0.35	0.41	0.40	0.40	0.35	0.45
Pixel RF	0.51	0.35	0.35	0.41	0.39	0.40	0.35	0.43
Pixel SVM	0.51	0.35	0.34	0.41	0.40	0.40	0.35	0.45

### Blekinge 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.40	0.18	-0.01	0.43	0.26	0.32	0.02	0.05
Object SVM	0.27	0.04	-0.03	0.34	0.20	0.25	0.26	0.27
Pixel RF	0.26	0.06	0.05	0.34	0.21	0.26	0.19	0.23
Pixel SVM	0.23	0.03	0.05	0.32	0.19	0.23	0.21	0.22

## Overlapping areas of validation polygons and created damage polygons

<i>Jönköping</i> <i>Area (m<sup>2</sup>)</i>	<i>Grid</i> <i>Object</i> <i>RF</i>	<i>Grid</i> <i>Object</i> <i>SVM</i>	<i>Grid</i> <i>Pixel</i> <i>RF</i>	<i>Grid</i> <i>Pixel</i> <i>SVM</i>	<i>No-Grid</i> <i>Object</i> <i>RF</i>	<i>No-Grid</i> <i>Object</i> <i>SVM</i>	<i>No-Grid</i> <i>Pixel</i> <i>RF</i>	<i>No-Grid</i> <i>Pixel</i> <i>SVM</i>
<i>Deer</i>	0	0	0	0	0	0	0	0
<i>Drought</i>	769	750	782	709	458	446	373	330
<i>Machine</i>	2737	2740	2697	2435	2078	2035	1778	1670
<i>Stone</i>	329	329	328	324	294	294	279	272
<i>Water</i>	5276	5185	5215	4810	3893	3666	3424	2784
<i>Wild boar</i>	1033	1004	1066	939	800	793	732	618

## Field evaluation Grass Grid / No-grid Jönköping 2024

### *Jönköping 2024, Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.54	0.34	0.38	0.44	0.41	0.27	0.53	0.36
<i>Object</i> <i>SVM</i>	0.54	0.34	0.39	0.44	0.41	0.28	0.55	0.37
<i>Pixel</i> <i>RF</i>	0.54	0.34	0.39	0.44	0.41	0.28	0.53	0.37
<i>Pixel</i> <i>SVM</i>	0.54	0.35	0.39	0.45	0.42	0.28	0.57	0.37

### *Jönköping 2024, No-Grid*

	<i>overall</i> <i>accuracy</i>	<i>overall</i> <i>kappa</i>	<i>overall</i> <i>precision</i>	<i>overall</i> <i>recall</i>	<i>overall</i> <i>F1score</i>	<i>wild boar</i> <i>precision</i>	<i>wild boar</i> <i>recall</i>	<i>wild boar</i> <i>F1score</i>
<i>Object</i> <i>RF</i>	0.51	0.17	0.43	0.26	0.32	0.16	0.31	0.21
<i>Object</i> <i>SVM</i>	0.52	0.21	0.29	0.23	0.26	0.15	0.28	0.20
<i>Pixel</i> <i>RF</i>	0.63	0.39	0.42	0.35	0.38	0.40	0.44	0.42
<i>Pixel</i> <i>SVM</i>	0.57	0.34	0.37	0.36	0.36	0.49	0.67	0.57



## Overlapping areas of validation polygons and created damage polygons

<b>Örebro Area (m<sup>2</sup>)</b>	<b>Grid Object RF</b>	<b>Grid Object SVM</b>	<b>Grid Pixel RF</b>	<b>Grid Pixel SVM</b>	<b>No-Grid Object RF</b>	<b>No-Grid Object SVM</b>	<b>No-Grid Pixel RF</b>	<b>No-Grid Pixel SVM</b>
Deer	497	439	522	534	270	233	183	203
Drought	1175	1176	1215	1221	846	863	682	818
Machine	1621	1626	1589	1511	1202	1196	1121	1058
Stone	144	144	144	144	141	141	136	135
Water	35822	34733	36605	34095	25577	24443	22559	17021
Wild boar	293	293	291	284	232	240	230	209

## Field evaluation Grass Grid / No-grid Örebro 2024

### Örebro 2024, Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.75	0.25	0.32	0.34	0.58	0.43	0.34	0.05
Object SVM	0.75	0.24	0.32	0.33	0.58	0.42	0.35	0.05
Pixel RF	0.76	0.24	0.32	0.33	0.58	0.42	0.34	0.05
Pixel SVM	0.76	0.26	0.32	0.34	0.58	0.43	0.34	0.05

### Örebro 2024, No-Grid

	<b>overall accuracy</b>	<b>overall kappa</b>	<b>overall precision</b>	<b>overall recall</b>	<b>overall F1score</b>	<b>wild boar precision</b>	<b>wild boar recall</b>	<b>wild boar F1score</b>
Object RF	0.59	0.05	-0.03	0.20	0.29	0.24	0.34	0.02
Object SVM	0.75	0.14	-0.04	0.27	0.35	0.31	0.34	0.03
Pixel RF	0.65	0.03	-0.01	0.22	0.24	0.23	0.34	0.05
Pixel SVM	0.59	0.04	0.00	0.27	0.30	0.29	0.43	0.03

## Overlapping areas of validation polygons and created damage polygons

<i>Södermanland Area (m<sup>2</sup>)</i>	<i>Grid Object RF</i>	<i>Grid Object SVM</i>	<i>Grid Pixel RF</i>	<i>Grid Pixel SVM</i>	<i>No-Grid Object RF</i>	<i>No-Grid Object SVM</i>	<i>No-Grid Pixel RF</i>	<i>No-Grid Pixel SVM</i>
<i>Deer</i>	24	25	24	22	19	19	15	12
<i>Drought</i>	827	890	895	921	426	475	360	439
<i>Machine</i>	1627	1626	1621	1619	1236	1296	1093	1180
<i>Stone</i>	110	111	110	110	108	108	107	107
<i>Water</i>	49030	48629	47526	45066	24728	24425	17204	17404
<i>Wild boar</i>	1359	1360	1360	1362	1248	1259	1168	1209

## Field evaluation Grass Grid / No-grid Södermanland 2024

### *Södermanland 2024, Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.76	0.17	0.25	0.23	0.42	0.30	0.42	0.13
<i>Object SVM</i>	0.76	0.17	0.25	0.23	0.42	0.30	0.42	0.13
<i>Pixel RF</i>	0.75	0.17	0.25	0.23	0.42	0.30	0.42	0.13
<i>Pixel SVM</i>	0.74	0.17	0.25	0.23	0.42	0.30	0.42	0.14

### *Södermanland 2024, No-Grid*

	<i>overall accuracy</i>	<i>overall kappa</i>	<i>overall precision</i>	<i>overall recall</i>	<i>overall F1score</i>	<i>wild boar precision</i>	<i>wild boar recall</i>	<i>wild boar F1score</i>
<i>Object RF</i>	0.75	-0.01	-0.08	0.17	0.21	0.18	0.01	0.01
<i>Object SVM</i>	0.76	0.00	-0.08	0.22	0.23	0.22	0.02	0.01
<i>Pixel RF</i>	0.61	0.04	-0.01	0.21	0.30	0.25	0.16	0.06
<i>Pixel SVM</i>	0.53	-0.06	-0.04	0.18	0.23	0.20	0.03	0.01

### 3. Post-classification Analysis – Damage Types ratios

#### Wheat – Jönköping damage types ratios

##### Wheat - Object-based Random Forest Damage Classification

**Table 1.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	846239m <sup>2</sup>	9616m <sup>2</sup>	10443m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 2.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.27</b>	0.27	0.01

**Table 3.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.25	0.01	0.15	0.28	0.16	0.31
<b>NO-GRID - Mean</b>	0.41	0.01	0.1	0.1	0.45	0.38
<b>GRID - Median</b>	0.24	0	0.13	0.27	0	0.28
<b>NO-GRID - Median</b>	0.38	0	0.05	0.06	0	0.38
<b>GRID - Variance</b>	0.02	0	0.01	0.04	1.12	0.05
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.01	3.08	0.03

**Table 4.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.07	0.12	0.04	0.08	0.98	0.07
<b>NO-GRID - Mean</b>	0.08	0.27	0.06	0.13	2.02	0.07
<b>GRID - Median</b>	0.06	0	0.03	0.06	0	0.06
<b>NO-GRID - Median</b>	0.06	0	0.01	0.01	0	0.06
<b>GRID - Variance</b>	0	0.56	0	0	6.99	0
<b>NO-GRID - Variance</b>	0	1.91	0.09	1	10.13	0

**Table 5.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.297	0.01	0.15	0.31	0	0.24
<b>NO-GRID - Mean</b>	0.462	0.01	0.11	0.11	0	0.32

**Table 6.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.08	0	0.04	0.08	0	0.06	0.73
<b>NO-GRID - Mean</b>	0.095	0	0.02	0.02	0	0.06	0.79

## Wheat Object-based Support Vector Machine Damage Classification

**Table 7.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	822171m <sup>2</sup>	9343m <sup>2</sup>	10361m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 8.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.26</b>	0.25	0.02

**Table 9.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.15	0.28	0.31	0.3
<b>NO-GRID - Mean</b>	0.44	0.1	0.06	0.12	0.16	0.38
<b>GRID - Median</b>	0.25	0	0.13	0.26	0	0.28
<b>NO-GRID - Median</b>	0.44	0	0.03	0.07	0	0.37
<b>GRID - Variance</b>	0.02	0	0.01	0.04	2.25	0.05
<b>NO-GRID - Variance</b>	0.04	0.79	0.01	0.02	0.78	0.03

**Table 10.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.6	0.04	0.07	1.03	0.06
<b>NO-GRID - Mean</b>	0.09	0.66	0.11	0.11	2.01	0.07
<b>GRID - Median</b>	0.06	0	0.03	0.06	0	0.06
<b>NO-GRID - Median</b>	0.06	0	0.01	0.01	0	0.06
<b>GRID - Variance</b>	0.01	4.4	0	0	6.51	0
<b>NO-GRID - Variance</b>	0.01	5.28	0.86	0.62	9.19	0

**Table 11.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.316	0.01	0.14	0.31	0	0.22
<b>NO-GRID - Mean</b>	0.445	0.01	0.05	0.16	0	0.34

**Table 12.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.083	0	0.04	0.08	0	0.06	0.74
<b>NO-GRID - Mean</b>	0.091	0	0.01	0.03	0	0.07	0.79

## Wheat Pixel-based Random Forest Damage Classification

**Table 13.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	468370m <sup>2</sup>	5322m <sup>2</sup>	5187m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 14.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.17</b>	0.16	0

**Table 15.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.23	0.01	0.18	0.26	0.08	0.32
<b>NO-GRID - Mean</b>	0.5	0.01	0.1	0.14	0.03	0.25
<b>GRID - Median</b>	0.22	0	0.16	0.23	0	0.28
<b>NO-GRID - Median</b>	0.52	0.01	0.05	0.08	0	0.22
<b>GRID - Variance</b>	0.02	0	0.01	0.04	0.53	0.05
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.02	0.06	0.02

**Table 16.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.12	0.15	0.03	0.04	0.68	0.05
<b>NO-GRID - Mean</b>	0.05	0.29	0.06	0.01	1.75	0.03
<b>GRID - Median</b>	0.03	0	0.02	0.03	0	0.04
<b>NO-GRID - Median</b>	0.04	0	0.01	0.01	0	0.02
<b>GRID - Variance</b>	0.53	0.81	0	0	3.39	0
<b>NO-GRID - Variance</b>	0	1.67	0.19	0	8.25	0

**Table 17.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.278	0.01	0.19	0.28	0	0.25
<b>NO-GRID - Mean</b>	0.506	0.02	0.08	0.15	0	0.25

**Table 18.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.042	0	0.03	0.04	0	0.04	0.85
<b>NO-GRID - Mean</b>	0.047	0	0.01	0.01	0	0.02	0.91

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 19.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the wheat fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>88</b>	492891m <sup>2</sup>	5601m <sup>2</sup>	7099m <sup>2</sup>	3121091m <sup>2</sup>	35467m <sup>2</sup>	35707m <sup>2</sup>

**Table 20.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0.01

**Table 21.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.24	0.01	0.18	0.25	0	0.32
<b>NO-GRID - Mean</b>	0.54	0.01	0.07	0.12	0.2	0.25
<b>GRID - Median</b>	0.25	0	0.17	0.21	0	0.29
<b>NO-GRID - Median</b>	0.56	0	0.04	0.06	0	0.24
<b>GRID - Variance</b>	0.02	0	0.01	0.04	0	0.05
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.02	1.38	0.02

**Table 22.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.71	0.03	0.04	0.71	0.05
<b>NO-GRID - Mean</b>	0.05	1.19	0.08	0.01	2.78	0.02
<b>GRID - Median</b>	0.03	0	0.02	0.03	0	0.04
<b>NO-GRID - Median</b>	0.04	0	0	0.01	1.77	0.02
<b>GRID - Variance</b>	0	4.19	0	0	3.69	0
<b>NO-GRID - Variance</b>	0	8.09	0.48	0	9.67	0

**Table 23.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.296	0.01	0.19	0.26	0	0.25
<b>NO-GRID - Mean</b>	0.57	0.01	0.07	0.12	0	0.22

**Table 24.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.047	0	0.03	0.04	0	0.04	0.84
<b>NO-GRID - Mean</b>	0.056	0	0.01	0.01	0	0.02	0.9



## Grass – Jönköping damage types ratios

### Grass - Object-based Random Forest Damage Classification

**Table 25.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	223426m <sup>2</sup>	2429m <sup>2</sup>	2311m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 26.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.25</b>	0.21	0.02

**Table 27.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.1	0.11	0.19	0.07	0.45
<b>NO-GRID - Mean</b>	0.15	0.04	0.03	0.11	0.1	0.65
<b>GRID - Median</b>	0.13	0.01	0.08	0.17	0.05	0.45
<b>NO-GRID - Median</b>	0.09	0.02	0.01	0.08	0	0.72
<b>GRID - Variance</b>	0.01	0.45	0.01	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.01	0.35	0.05

**Table 28.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.31	0.07	0.04	0.01	0.1
<b>NO-GRID - Mean</b>	0.02	0.08	0.16	0.01	0.65	0.11
<b>GRID - Median</b>	0.02	0	0.01	0.02	0.01	0.06
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.06
<b>GRID - Variance</b>	0	2.25	0.15	0	0	0.01
<b>NO-GRID - Variance</b>	0	0.6	0.78	0	3.72	0.02

**Table 29.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.151	0.03	0.11	0.19	0.05	0.46
<b>NO-GRID - Mean</b>	0.122	0.03	0.04	0.11	0	0.7

**Table 30.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.025	0.01	0.02	0.03	0.01	0.08	0.84
<b>NO-GRID - Mean</b>	0.015	0	0	0.01	0	0.09	0.88

## Grass - Object-based Support Vector Machine Damage Classification

**Table 31.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	170841m <sup>2</sup>	1857m <sup>2</sup>	1682m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 32.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.21</b>	0.17	0.02

**Table 33.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.09	0.11	0.19	0.07	0.45
<b>NO-GRID - Mean</b>	0.18	0.05	0.02	0.13	0.1	0.61
<b>GRID - Median</b>	0.14	0.01	0.08	0.16	0.05	0.45
<b>NO-GRID - Median</b>	0.13	0.03	0	0.09	0	0.65
<b>GRID - Variance</b>	0.01	0.43	0.01	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.01	0.7	0.04

**Table 34.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.17	0.02	0.03	0.01	0.08
<b>NO-GRID - Mean</b>	0.02	0	0.26	0.01	0.79	0.08
<b>GRID - Median</b>	0.02	0	0.01	0.02	0.01	0.05
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.05
<b>GRID - Variance</b>	0	0.87	0	0	0	0.01
<b>NO-GRID - Variance</b>	0	0	1.73	0	4.45	0.01

**Table 35.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.03	0.11	0.19	0.06	0.45
<b>NO-GRID - Mean</b>	0.16	0.05	0.04	0.12	0.01	0.62

**Table 36.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.019	0	0.01	0.02	0.01	0.06	0.87
<b>NO-GRID - Mean</b>	0.015	0	0	0.01	0	0.06	0.91

## Grass – Pixel-based Random Forest Damage Classification

**Table 37.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>92</b>	160277m <sup>2</sup>	1742m <sup>2</sup>	1935m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 38.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.17</b>	0.1	0.03

**Table 39.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.14	0.03	0.11	0.18	0.06	0.48
<b>NO-GRID - Mean</b>	0.15	0.05	0.03	0.2	0.1	0.56
<b>GRID - Median</b>	0.12	0.01	0.08	0.15	0.04	0.48
<b>NO-GRID - Median</b>	0.1	0.01	0	0.17	0.01	0.58
<b>GRID - Variance</b>	0.01	0	0.01	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.02	0.02	0.01	0.03	0.76	0.06

**Table 40.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.24	0.02	0.02	0.01	0.08
<b>NO-GRID - Mean</b>	0.01	0.47	0.86	0.01	0.6	0.08
<b>GRID - Median</b>	0.01	0	0.01	0.02	0	0.04
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	1.22	0	0	0	0.01
<b>NO-GRID - Variance</b>	0	3.72	5.85	0	4.04	0.02

**Table 41.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<i>Ratio</i>						
<i>Predicted damages</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>GRID - Mean</i>	0.131	0.04	0.11	0.16	0.05	0.51
<i>NO-GRID - Mean</i>	0.1	0.04	0.05	0.16	0.01	0.65

**Table 42.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<i>Ratio</i>							
<i>Total field area</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>	<i>No damage</i>
<i>GRID - Mean</i>	0.015	0	0.01	0.02	0.01	0.06	0.88
<i>NO-GRID - Mean</i>	0.009	0	0	0.01	0	0.06	0.91

## Grass - Pixel-based Support Vector Machine Damage Classification

**Table 43.** The total fields predicted in Jönköping, together with the total area, and mean and standard deviation of the grass fields in Jönköping, of the predicted damage and field area.

<i>Total Field Predicted</i>	<i>Damage Area Total</i>	<i>Damage Area Mean</i>	<i>Damage Area Standard Deviation</i>	<i>Field Area Total</i>	<i>Field Area Mean</i>	<i>Field Area Standard Deviation</i>
92	57006m <sup>2</sup>	620m <sup>2</sup>	906m <sup>2</sup>	1357107m <sup>2</sup>	14751m <sup>2</sup>	15863m <sup>2</sup>

**Table 44.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Jönköping study area.

<i>Ratio Damage vs Field Area Mean</i>	<i>Ratio Damage vs Field Area Median</i>	<i>Ratio Damage vs Field Area Variance</i>
0.06	0.03	0

**Table 45.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<i>Ratio</i>						
<i>Predicted damage</i>	<i>Wild boar</i>	<i>Deer</i>	<i>Drought</i>	<i>Machine</i>	<i>Stone</i>	<i>Water</i>
<i>GRID - Mean</i>	0.16	0.02	0.11	0.2	0.08	0.43
<i>NO-GRID - Mean</i>	0.23	0.02	0.03	0.22	0.05	0.45
<i>GRID - Median</i>	0.13	0	0.08	0.15	0.05	0.42
<i>NO-GRID - Median</i>	0.17	0.01	0	0.19	0.02	0.47
<i>GRID - Variance</i>	0.02	0	0.01	0.03	0.01	0.05
<i>NO-GRID - Variance</i>	0.03	0	0.01	0.04	0	0.05

**Table 46.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.1	0.78	0.58	0.1	0.38	0.02
<b>NO-GRID - Mean</b>	0.01	1.78	0.55	0.26	0.37	0.1
<b>GRID - Median</b>	0	0	0	0	0	0.01
<b>NO-GRID - Median</b>	0	0	0	0	0	0.01
<b>GRID - Variance</b>	0.81	4.41	4.2	0.79	2.78	0
<b>NO-GRID - Variance</b>	0	8.79	3.74	2.06	2.26	0.6

**Table 47.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.146	0.04	0.11	0.17	0.07	0.46
<b>NO-GRID - Mean</b>	0.19	0.02	0.07	0.19	0.02	0.52

**Table 48.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.006	0	0	0.01	0	0.02	0.96
<b>NO-GRID - Mean</b>	0.006	0	0	0.01	0	0.02	0.97

## Wheat – Blekinge damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 49.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	274024m <sup>2</sup>	4725m <sup>2</sup>	3905m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 50.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0.01

**Table 51.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.14	0.35	0.23	0.23
<b>NO-GRID - Mean</b>	0.47	0.01	0.07	0.14	0	0.3
<b>GRID - Median</b>	0.21	0.01	0.08	0.36	0	0.18
<b>NO-GRID - Median</b>	0.43	0.01	0.05	0.12	0	0.3
<b>GRID - Variance</b>	0.03	0	0.02	0.04	1.75	0.03
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.02	0	0.02

**Table 52.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.04	0.02	0.17	1.47	0.03
<b>NO-GRID - Mean</b>	0.06	0.33	0.01	0.01	1.41	0.03
<b>GRID - Median</b>	0.03	0	0.01	0.04	0	0.02
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	0.08	0	0.81	7.83	0
<b>NO-GRID - Variance</b>	0	2.26	0	0	8.99	0

**Table 53.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.267	0.01	0.13	0.4	0	0.19
<b>NO-GRID - Mean</b>	0.441	0.01	0.09	0.18	0	0.27

**Table 54.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.035	0	0.02	0.05	0	0.02	0.87
<b>NO-GRID - Mean</b>	0.045	0	0.01	0.02	0	0.03	0.9

## Wheat Object-based Support Vector Machine Damage Classification

**Table 55.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	340475m <sup>2</sup>	5870m <sup>2</sup>	5472m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 56.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.18</b>	0.15	0.01

**Table 57.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.26	0.01	0.13	0.36	0.51	0.24
<b>NO-GRID - Mean</b>	0.47	0.02	0.05	0.15	0	0.31
<b>GRID - Median</b>	0.22	0.01	0.09	0.35	0	0.19
<b>NO-GRID - Median</b>	0.44	0.01	0.03	0.1	0	0.31
<b>GRID - Variance</b>	0.03	0	0.02	0.04	3.44	0.03
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.02	0	0.03

**Table 58.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0	0.02	0.06	1.82	0.04
<b>NO-GRID - Mean</b>	0.06	0.12	0.23	0.02	1.63	0.04
<b>GRID - Median</b>	0.03	0	0.01	0.05	0	0.03
<b>NO-GRID - Median</b>	0.05	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	0	0	0	9.4	0
<b>NO-GRID - Variance</b>	0	0.33	1.73	0	11.35	0



**Table 59.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.271	0.01	0.13	0.41	0	0.17
<b>NO-GRID - Mean</b>	0.439	0.02	0.08	0.16	0	0.3

**Table 60.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.044	0	0.02	0.07	0	0.03	0.84
<b>NO-GRID - Mean</b>	0.056	0	0.01	0.02	0	0.04	0.87

## Wheat Pixel-based Random Forest Damage Classification

**Table 61.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	149803m <sup>2</sup>	2583m <sup>2</sup>	2231m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 62.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.08</b>	0.08	0

**Table 63.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.28	0.01	0.14	0.31	0	0.26
<b>NO-GRID - Mean</b>	0.6	0.15	0.03	0.19	0.01	0.15
<b>GRID - Median</b>	0.23	0.01	0.11	0.32	0	0.21
<b>NO-GRID - Median</b>	0.64	0	0.01	0.15	0.01	0.14
<b>GRID - Variance</b>	0.04	0	0.02	0.03	0	0.03
<b>NO-GRID - Variance</b>	0.03	1.04	0	0.02	0	0.02

**Table 64.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.38	0.01	0.02	1.14	0.02
<b>NO-GRID - Mean</b>	0.03	1.9	0.19	0.01	1.3	0.08
<b>GRID - Median</b>	0.01	0	0.01	0.02	0	0.02
<b>NO-GRID - Median</b>	0.03	0	0	0.01	0	0.01
<b>GRID - Variance</b>	0	2.71	0	0	4.09	0
<b>NO-GRID - Variance</b>	0	8.35	0.59	0	8.36	0.34

**Table 65.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.273	0.02	0.16	0.35	0	0.21
<b>NO-GRID - Mean</b>	0.568	0.01	0.03	0.2	0.01	0.18

**Table 66.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0.01	0.02	0	0.01	0.93
<b>NO-GRID - Mean</b>	0.026	0	0	0.01	0	0.01	0.95

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 67.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the wheat fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>58</b>	114222m <sup>2</sup>	1969m <sup>2</sup>	1787m <sup>2</sup>	2083453m <sup>2</sup>	35922m <sup>2</sup>	30256m <sup>2</sup>

**Table 68.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.07</b>	0.06	0

**Table 69.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.29	0.02	0.1	0.3	0	0.29
<b>NO-GRID - Mean</b>	0.62	0.03	0.02	0.19	0.01	0.13
<b>GRID - Median</b>	0.25	0.01	0.05	0.3	0	0.23
<b>NO-GRID - Median</b>	0.66	0	0	0.16	0.01	0.11
<b>GRID - Variance</b>	0.04	0	0.01	0.04	0	0.04
<b>NO-GRID - Variance</b>	0.04	0.01	0	0.03	0	0.01

**Table 70.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.48	0	0.02	1.17	0.02
<b>NO-GRID - Mean</b>	0.03	1.77	0.83	0.01	1.08	0.11
<b>GRID - Median</b>	0.01	0	0	0.01	0	0.01
<b>NO-GRID - Median</b>	0.02	0.01	0	0.01	0	0
<b>GRID - Variance</b>	0	3.2	0	0	5.18	0
<b>NO-GRID - Variance</b>	0	5.96	5.83	0	6.28	0.61

**Table 71.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.298	0.02	0.09	0.35	0	0.24
<b>NO-GRID - Mean</b>	0.597	0.01	0.02	0.21	0.01	0.15

**Table 72.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.016	0	0.01	0.02	0	0.01	0.95
<b>NO-GRID - Mean</b>	0.022	0	0	0.01	0	0.01	0.96

## Grass – Blekinge damage types ratios

### Grass - Object-based Random Forest Damage Classification

**Table 73.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	153982m <sup>2</sup>	2139m <sup>2</sup>	1772m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 74.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.28</b>	0.22	0.06

**Table 75.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.19	0.15	0.11	0.17	0.1	0.41
<b>NO-GRID - Mean</b>	0.17	0.03	0.03	0.11	0.01	0.65
<b>GRID - Median</b>	0.18	0.01	0.07	0.11	0.06	0.35
<b>NO-GRID - Median</b>	0.1	0.02	0	0.07	0	0.72
<b>GRID - Variance</b>	0.01	1.18	0.01	0.03	0.01	0.04
<b>NO-GRID - Variance</b>	0.04	0	0.01	0.02	0	0.05

**Table 76.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.06	0.03	0.03	0.03	0.02	0.09
<b>NO-GRID - Mean</b>	0.04	0.22	0.34	0.02	0.48	0.1
<b>GRID - Median</b>	0.03	0	0.01	0.02	0.01	0.07
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.08
<b>GRID - Variance</b>	0.02	0.02	0	0	0	0.01
<b>NO-GRID - Variance</b>	0.01	1.75	2.67	0	2.99	0.01

**Table 77.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.187	0.03	0.1	0.21	0.11	0.37
<b>NO-GRID - Mean</b>	0.226	0.03	0.03	0.11	0.01	0.6

**Table 78.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.032	0.01	0.02	0.04	0.02	0.06	0.83
<b>NO-GRID - Mean</b>	0.029	0	0	0.01	0	0.08	0.87

## Grass - Object-based Support Vector Machine Damage Classification

**Table 79.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	153283m <sup>2</sup>	2129m <sup>2</sup>	1774m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 80.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.27</b>	0.22	0.06

**Table 81.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.19	0.22	0.11	0.16	0.09	0.42
<b>NO-GRID - Mean</b>	0.16	0.03	0.02	0.12	0.01	0.66
<b>GRID - Median</b>	0.17	0.01	0.06	0.1	0.05	0.37
<b>NO-GRID - Median</b>	0.09	0.02	0	0.05	0	0.72
<b>GRID - Variance</b>	0.01	1.37	0.01	0.03	0.01	0.04
<b>NO-GRID - Variance</b>	0.03	0	0	0.04	0	0.05

**Table 82.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.06	0.15	0.03	0.03	0.02	0.09
<b>NO-GRID - Mean</b>	0.03	0.15	0.16	0.02	1.09	0.12
<b>GRID - Median</b>	0.03	0	0.01	0.02	0.01	0.06
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.1
<b>GRID - Variance</b>	0.01	1.02	0	0	0	0.01
<b>NO-GRID - Variance</b>	0	0.79	1.09	0	6.98	0.02

**Table 83.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.193	0.04	0.11	0.19	0.1	0.37
<b>NO-GRID - Mean</b>	0.179	0.03	0.02	0.16	0	0.61

**Table 84.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.033	0.01	0.02	0.03	0.02	0.06	0.83
<b>NO-GRID - Mean</b>	0.024	0	0	0.02	0	0.08	0.87

## Grass – Pixel-based Random Forest Damage Classification

**Table 85.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	95349m <sup>2</sup>	1324m <sup>2</sup>	1136m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 86.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.17</b>	0.12	0.03

**Table 87.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.18	0.03	0.13	0.16	0.08	0.42
<b>NO-GRID - Mean</b>	0.23	0.02	0.02	0.18	0.02	0.53
<b>GRID - Median</b>	0.16	0.01	0.08	0.1	0.05	0.39
<b>NO-GRID - Median</b>	0.13	0.01	0	0.13	0.01	0.56
<b>GRID - Variance</b>	0.01	0	0.02	0.03	0.01	0.04
<b>NO-GRID - Variance</b>	0.05	0	0	0.03	0	0.05

**Table 88.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.4	0.03	0.02	0.01	0.06
<b>NO-GRID - Mean</b>	0.03	0.41	0.19	0.02	0.14	0.06
<b>GRID - Median</b>	0.02	0	0.01	0.01	0.01	0.04
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	2.65	0	0	0	0
<b>NO-GRID - Variance</b>	0	3.33	1.21	0	0.7	0

**Table 89.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.188	0.04	0.13	0.18	0.08	0.38
<b>NO-GRID - Mean</b>	0.266	0.02	0.02	0.21	0.01	0.47

**Table 90.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0.01	0.02	0.01	0.04	0.89
<b>NO-GRID - Mean</b>	0.02	0	0	0.02	0	0.04	0.92

## Grass - Pixel-based Support Vector Machine Damage Classification

**Table 91.** The total fields predicted in Blekinge, together with the total area, and mean and standard deviation of the grass fields in Blekinge, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>72</b>	80792m <sup>2</sup>	1122m <sup>2</sup>	1119m <sup>2</sup>	905485m <sup>2</sup>	12576m <sup>2</sup>	12998m <sup>2</sup>

**Table 92.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Blekinge study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.15</b>	0.1	0.02

**Table 93.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.19	0.11	0.12	0.15	0.08	0.42
<b>NO-GRID - Mean</b>	0.26	0.15	0.03	0.16	0.02	0.5
<b>GRID - Median</b>	0.17	0.01	0.08	0.08	0.05	0.39
<b>NO-GRID - Median</b>	0.23	0	0	0.13	0.01	0.52
<b>GRID - Variance</b>	0.01	0.62	0.02	0.03	0.01	0.04
<b>NO-GRID - Variance</b>	0.04	1.29	0.01	0.02	0	0.05



**Table 94.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.8	0.33	0.02	0.01	0.05
<b>NO-GRID - Mean</b>	0.17	1.17	0.18	0.14	0.07	0.05
<b>GRID - Median</b>	0.02	0	0.01	0.01	0	0.04
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0	4.8	2.25	0	0	0
<b>NO-GRID - Variance</b>	1.27	6.84	1.09	1.13	0.19	0

**Table 95.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.193	0.04	0.14	0.17	0.08	0.38
<b>NO-GRID - Mean</b>	0.267	0.02	0.03	0.18	0.01	0.5

**Table 96.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.017	0	0.01	0.02	0.01	0.03	0.91
<b>NO-GRID - Mean</b>	0.018	0	0	0.01	0	0.03	0.93

## Wheat – Örebro damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 97.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	574950m <sup>2</sup>	6388m <sup>2</sup>	4703m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 98.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.25</b>	<b>0.2</b>	<b>0.05</b>

**Table 99.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.23	0.02	0.15	0.44	0.07	0.17
<b>NO-GRID - Mean</b>	0.42	0.01	0.12	0.22	0.07	0.23
<b>GRID - Median</b>	0.18	0	0.1	0.45	0	0.12
<b>NO-GRID - Median</b>	0.4	0.01	0.07	0.19	0	0.22
<b>GRID - Variance</b>	0.02	0.02	0.02	0.05	0.23	0.02
<b>NO-GRID - Variance</b>	0.04	0	0.02	0.03	0.41	0.02

**Table 100.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.33	0.04	0.1	0.7	0.04
<b>NO-GRID - Mean</b>	0.07	0.05	0.11	0.03	2.89	0.04
<b>GRID - Median</b>	0.03	0	0.02	0.08	0	0.02
<b>NO-GRID - Median</b>	0.05	0	0.01	0.02	2.14	0.03
<b>GRID - Variance</b>	0	2.22	0	0.01	5.18	0
<b>NO-GRID - Variance</b>	0	0.18	0.66	0	10.25	0

**Table 101.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.29	0.02	0.13	0.42	0	0.13
<b>NO-GRID - Mean</b>	0.427	0.02	0.12	0.21	0	0.23

**Table 102.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.058	0	0.03	0.08	0	0.03	0.8
<b>NO-GRID - Mean</b>	0.064	0	0.02	0.03	0	0.03	0.85

## Wheat Object-based Support Vector Machine Damage Classification

**Table 103.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	528531m <sup>2</sup>	5873m <sup>2</sup>	4405m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 104.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.22</b>	0.18	0.05

**Table 105.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.23	0.01	0.15	0.46	0.28	0.16
<b>NO-GRID - Mean</b>	0.39	0.01	0.12	0.22	0.16	0.25
<b>GRID - Median</b>	0.18	0	0.1	0.46	0	0.1
<b>NO-GRID - Median</b>	0.37	0.01	0.07	0.21	0	0.23
<b>GRID - Variance</b>	0.02	0	0.02	0.05	1.52	0.02
<b>NO-GRID - Variance</b>	0.03	0	0.02	0.03	0.94	0.02

**Table 106.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.45	0.03	0.09	0.97	0.03
<b>NO-GRID - Mean</b>	0.06	0.1	0.08	0.03	2.6	0.04
<b>GRID - Median</b>	0.03	0	0.02	0.08	0	0.02
<b>NO-GRID - Median</b>	0.05	0	0.01	0.03	1.12	0.03
<b>GRID - Variance</b>	0	2.37	0	0.01	6.44	0
<b>NO-GRID - Variance</b>	0	0.47	0.27	0	9.61	0

**Table 107.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.286	0.02	0.13	0.44	0	0.12
<b>NO-GRID - Mean</b>	0.414	0.01	0.12	0.21	0	0.24

**Table 108.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.053	0	0.02	0.08	0	0.02	0.82
<b>NO-GRID - Mean</b>	0.059	0	0.02	0.03	0	0.03	0.86

## Wheat Pixel-based Random Forest Damage Classification

**Table 109.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	215817m <sup>2</sup>	2398m <sup>2</sup>	1912m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 110.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.1</b>	0.08	0.01

**Table 111.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.22	0.01	0.19	0.43	0	0.16
<b>NO-GRID - Mean</b>	0.35	0.02	0.11	0.34	0.1	0.17
<b>GRID - Median</b>	0.18	0	0.15	0.4	0	0.1
<b>NO-GRID - Median</b>	0.35	0.02	0.03	0.33	0	0.1
<b>GRID - Variance</b>	0.02	0	0.02	0.05	0	0.02
<b>NO-GRID - Variance</b>	0.03	0	0.03	0.04	0.86	0.03

**Table 112.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	0.96	0.02	0.03	1.15	0.01
<b>NO-GRID - Mean</b>	0.02	0.5	0.38	0.02	2.96	0.15
<b>GRID - Median</b>	0.01	0	0.01	0.03	0	0.01
<b>NO-GRID - Median</b>	0.02	0	0	0.02	2.42	0.01
<b>GRID - Variance</b>	0	4.64	0	0	6.31	0
<b>NO-GRID - Variance</b>	0	3.48	1.68	0	8.86	0.96

**Table 113.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.268	0.01	0.19	0.39	0	0.13
<b>NO-GRID - Mean</b>	0.348	0.03	0.12	0.31	0	0.19

**Table 114.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.02	0	0.01	0.03	0	0.01	0.92
<b>NO-GRID - Mean</b>	0.018	0	0.01	0.02	0	0.01	0.95

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 115.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the wheat fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>90</b>	226896m <sup>2</sup>	2521m <sup>2</sup>	2308m <sup>2</sup>	2860978m <sup>2</sup>	31789m <sup>2</sup>	17761m <sup>2</sup>

**Table 116.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.1</b>	0.08	0.01

**Table 117.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.21	0.01	0.2	0.41	0	0.16
<b>NO-GRID - Mean</b>	0.37	0.01	0.09	0.32	0.09	0.21
<b>GRID - Median</b>	0.18	0	0.18	0.4	0	0.11
<b>NO-GRID - Median</b>	0.36	0.01	0.03	0.29	0	0.13
<b>GRID - Variance</b>	0.02	0	0.02	0.05	0	0.02
<b>NO-GRID - Variance</b>	0.03	0	0.02	0.04	0.72	0.03

**Table 118.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.02	1.04	0.02	0.03	1.11	0.01
<b>NO-GRID - Mean</b>	0.02	0.87	0.5	0.02	2.64	0.02
<b>GRID - Median</b>	0.01	0	0.01	0.03	0	0.01
<b>NO-GRID - Median</b>	0.01	0	0	0.01	1.62	0.01
<b>GRID - Variance</b>	0	5.25	0	0	5.7	0
<b>NO-GRID - Variance</b>	0	5.97	2.84	0	8.6	0

**Table 119.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.263	0.02	0.21	0.37	0	0.13
<b>NO-GRID - Mean</b>	0.385	0.02	0.09	0.28	0	0.22

**Table 120.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.021	0	0.02	0.03	0	0.01	0.92
<b>NO-GRID - Mean</b>	0.02	0	0	0.01	0	0.01	0.95

## Grass – Örebro damage types ratios

### Grass - Object-based Random Forest Damage Classification

**Table 121.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the grass fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	429866m <sup>2</sup>	4525m <sup>2</sup>	5040m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 122.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.24	0.05

**Table 123.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.13	0.11	0.11	0.12	0.04	0.58
<b>NO-GRID - Mean</b>	0.16	0.24	0.16	0.2	0.11	0.73
<b>GRID - Median</b>	0.11	0.01	0.09	0.07	0.01	0.61
<b>NO-GRID - Median</b>	0.08	0.01	0.01	0.06	0	0.72
<b>GRID - Variance</b>	0.01	0.7	0.01	0.02	0.01	0.04
<b>NO-GRID - Variance</b>	0.05	1.23	0.79	0.43	0.76	0.62

**Table 124.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.13	0.15	0.03	0	0.17
<b>NO-GRID - Mean</b>	0.05	0.29	0.39	0.09	0.6	0.21
<b>GRID - Median</b>	0.02	0	0.02	0.01	0	0.12
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.1
<b>GRID - Variance</b>	0	0.88	0.65	0.01	0	0.02
<b>NO-GRID - Variance</b>	0.01	1.78	2.58	0.2	3.93	0.5

**Table 125.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.102	0.02	0.1	0.11	0.02	0.65
<b>NO-GRID - Mean</b>	0.22	0.02	0.14	0.08	0	0.55

**Table 126.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.022	0	0.02	0.02	0	0.14	0.78
<b>NO-GRID - Mean</b>	0.04	0	0.02	0.01	0	0.1	0.82

## Grass - Object-based Support Vector Machine Damage Classification

**Table 127.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the grass fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	407910m <sup>2</sup>	4294m <sup>2</sup>	4775m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 128.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.26	0.05

**Table 129.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.13	0.24	0.1	0.12	0.04	0.58
<b>NO-GRID - Mean</b>	0.15	0.18	0.13	0.16	0.16	0.67
<b>GRID - Median</b>	0.12	0.01	0.07	0.07	0.02	0.6
<b>NO-GRID - Median</b>	0.08	0.02	0	0.05	0	0.73
<b>GRID - Variance</b>	0.01	1.57	0.01	0.02	0.01	0.04
<b>NO-GRID - Variance</b>	0.05	0.87	0.76	0.58	1.04	0.07



**Table 130.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.11	0.11	0.03	0	0.17
<b>NO-GRID - Mean</b>	0.05	0.32	0.42	0.08	0.97	0.15
<b>GRID - Median</b>	0.02	0	0.01	0.01	0	0.11
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.09
<b>GRID - Variance</b>	0	0.43	0.57	0.01	0	0.02
<b>NO-GRID - Variance</b>	0.01	1.99	2.65	0.45	6.13	0.03

**Table 131.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.11	0.02	0.1	0.12	0.02	0.63
<b>NO-GRID - Mean</b>	0.203	0.02	0.13	0.07	0	0.58

**Table 132.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.022	0	0.02	0.02	0	0.13	0.79
<b>NO-GRID - Mean</b>	0.035	0	0.02	0.01	0	0.1	0.83

## Grass – Pixel-based Random Forest Damage Classification

**Table 133.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the grass fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	328348m <sup>2</sup>	3456m <sup>2</sup>	3851m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 134.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.21</b>	0.16	0.03

**Table 135.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.12	0.03	0.11	0.12	0.03	0.59
<b>NO-GRID - Mean</b>	0.22	0.13	0.05	0.19	0.08	0.54
<b>GRID - Median</b>	0.09	0.01	0.08	0.07	0.02	0.6
<b>NO-GRID - Median</b>	0.13	0.01	0	0.14	0.01	0.56
<b>GRID - Variance</b>	0.01	0	0.01	0.02	0	0.03
<b>NO-GRID - Variance</b>	0.05	0.95	0.02	0.14	0.43	0.06

**Table 136.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.32	0.12	0.02	0.07	0.12
<b>NO-GRID - Mean</b>	0.04	0.74	0.67	0.04	0.6	0.09
<b>GRID - Median</b>	0.01	0	0.01	0.01	0	0.09
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.04
<b>GRID - Variance</b>	0	2.19	0.92	0	0.45	0.01
<b>NO-GRID - Variance</b>	0.01	4.84	4.84	0.07	3.03	0.01

**Table 137.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.107	0.02	0.11	0.12	0.02	0.63
<b>NO-GRID - Mean</b>	0.234	0.01	0.12	0.11	0.01	0.51

**Table 138.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.018	0	0.02	0.02	0	0.1	0.83
<b>NO-GRID - Mean</b>	0.028	0	0.01	0.01	0	0.06	0.88

## Grass - Pixel-based Support Vector Machine Damage Classification

**Table 139.** The total fields predicted in Örebro, together with the total area, and mean and standard deviation of the grass fields in Örebro, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>95</b>	247558m <sup>2</sup>	2606m <sup>2</sup>	3485m <sup>2</sup>	1989344m <sup>2</sup>	20940m <sup>2</sup>	20004m <sup>2</sup>

**Table 140.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Örebro study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	<b>0.11</b>	<b>0.03</b>

**Table 141.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.12	0.24	0.11	0.12	0.03	0.59
<b>NO-GRID - Mean</b>	0.25	0.26	0.05	0.22	0.02	0.47
<b>GRID - Median</b>	0.1	0.01	0.09	0.07	0.01	0.61
<b>NO-GRID - Median</b>	0.16	0.01	0.01	0.14	0.01	0.44
<b>GRID - Variance</b>	0.01	1.54	0.01	0.02	0	0.04
<b>NO-GRID - Variance</b>	0.05	1.69	0.02	0.22	0	0.06

**Table 142.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.71	0.31	0.1	0.22	0.09
<b>NO-GRID - Mean</b>	0.13	0.93	0.34	0.15	0.92	0.13
<b>GRID - Median</b>	0.01	0	0.01	0.01	0	0.06
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.03
<b>GRID - Variance</b>	0.95	3.48	2.55	0.48	1.22	0.01
<b>NO-GRID - Variance</b>	0.47	4.89	2.41	1.01	6.57	0.53

**Table 143.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.114	0.02	0.12	0.12	0.02	0.6
<b>NO-GRID - Mean</b>	0.254	0.02	0.16	0.11	0.01	0.44

**Table 144.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.014	0	0.02	0.02	0	0.07	0.88
<b>NO-GRID - Mean</b>	0.025	0	0.02	0.01	0	0.04	0.9

## Wheat – Södermanland damage types ratios

### Wheat - Object-based Random Forest Damage Classification

**Table 145.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	535732m <sup>2</sup>	15307m <sup>2</sup>	21235m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 146.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.29</b>	0.23	0.02

**Table 147.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.28	0.02	0.19	0.24	0.34	0.27
<b>NO-GRID - Mean</b>	0.43	0.01	0.07	0.07	0.28	0.42
<b>GRID - Median</b>	0.25	0.01	0.16	0.19	0	0.19
<b>NO-GRID - Median</b>	0.45	0	0.01	0.04	0	0.38
<b>GRID - Variance</b>	0.03	0	0.01	0.04	2.23	0.04
<b>NO-GRID - Variance</b>	0.05	0	0.03	0.01	2.64	0.05

**Table 148.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.19	0.05	0.06	0.74	0.07
<b>NO-GRID - Mean</b>	0.09	0.14	0.54	0.01	3.56	0.09
<b>GRID - Median</b>	0.06	0	0.04	0.04	0	0.05
<b>NO-GRID - Median</b>	0.06	0	0	0.01	4.08	0.06
<b>GRID - Variance</b>	0.01	1.14	0	0	4.71	0
<b>NO-GRID - Variance</b>	0.01	0.71	3.22	0	12.59	0.01

**Table 149.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.323	0.02	0.19	0.26	0	0.2
<b>NO-GRID - Mean</b>	0.421	0.01	0.04	0.08	0	0.45

**Table 150.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.079	0.01	0.05	0.06	0	0.05	0.76
<b>NO-GRID - Mean</b>	0.077	0	0.01	0.02	0	0.08	0.82

## Wheat Object-based Support Vector Machine Damage Classification

**Table 151.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	514574m <sup>2</sup>	14702m <sup>2</sup>	21318m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 152.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.26</b>	0.21	0.02

**Table 153.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.28	0.02	0.18	0.25	0.52	0.27
<b>NO-GRID - Mean</b>	0.42	0.22	0.08	0.07	0.5	0.42
<b>GRID - Median</b>	0.26	0.01	0.15	0.19	0	0.18
<b>NO-GRID - Median</b>	0.47	0	0.03	0.04	0	0.39
<b>GRID - Variance</b>	0.03	0	0.01	0.04	2.4	0.04
<b>NO-GRID - Variance</b>	0.05	1.69	0.04	0.01	4.26	0.05

**Table 154.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.08	0.01	0.05	0.05	1.13	0.06
<b>NO-GRID - Mean</b>	0.08	0.54	0.17	0.01	2.18	0.08
<b>GRID - Median</b>	0.06	0	0.03	0.04	0	0.04
<b>NO-GRID - Median</b>	0.05	0	0	0.01	0	0.06
<b>GRID - Variance</b>	0.01	0	0	0	6.41	0
<b>NO-GRID - Variance</b>	0	2.68	0.76	0	9.09	0.01

**Table 155.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.332	0.03	0.19	0.27	0	0.19
<b>NO-GRID - Mean</b>	0.453	0	0.07	0.09	0	0.39

**Table 156.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.078	0.01	0.04	0.06	0	0.04	0.77
<b>NO-GRID - Mean</b>	0.081	0	0.01	0.02	0	0.07	0.82

## Wheat Pixel-based Random Forest Damage Classification

**Table 157.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	319425m <sup>2</sup>	9126m <sup>2</sup>	13113m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 158.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.15	0.01

**Table 159.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.27	0.02	0.2	0.21	0	0.3
<b>NO-GRID - Mean</b>	0.57	0.02	0.04	0.18	0	0.2
<b>GRID - Median</b>	0.25	0.01	0.18	0.15	0	0.22
<b>NO-GRID - Median</b>	0.65	0	0.01	0.07	0	0.2
<b>GRID - Variance</b>	0.03	0	0.01	0.03	0	0.05
<b>NO-GRID - Variance</b>	0.05	0	0.01	0.05	0	0.02

**Table 160.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.19	0.03	0.03	0.99	0.05
<b>NO-GRID - Mean</b>	0.04	0.81	0.61	0.02	1.81	0.01
<b>GRID - Median</b>	0.03	0	0.02	0.02	0	0.04
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.01
<b>GRID - Variance</b>	0	1.22	0	0	7.27	0
<b>NO-GRID - Variance</b>	0	6.09	3.02	0	8.45	0

**Table 161.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.296	0.02	0.22	0.24	0	0.23
<b>NO-GRID - Mean</b>	0.576	0.01	0.02	0.22	0	0.18

**Table 162.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.043	0	0.03	0.03	0	0.03	0.85
<b>NO-GRID - Mean</b>	0.044	0	0	0.02	0	0.01	0.92

## Wheat Pixel-based Support Vector Machine Damage Classification

**Table 163.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the wheat fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>35</b>	360601m <sup>2</sup>	10303m <sup>2</sup>	17534m <sup>2</sup>	2196983m <sup>2</sup>	62771m <sup>2</sup>	90820m <sup>2</sup>

**Table 164.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.16</b>	0.14	0



**Table 165.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.27	0.02	0.21	0.21	0	0.29
<b>NO-GRID - Mean</b>	0.57	0.01	0.05	0.13	0.27	0.24
<b>GRID - Median</b>	0.24	0.01	0.2	0.16	0	0.2
<b>NO-GRID - Median</b>	0.62	0	0.02	0.1	0	0.21
<b>GRID - Variance</b>	0.03	0	0.01	0.03	0	0.05
<b>NO-GRID - Variance</b>	0.04	0	0	0.02	2.41	0.02

**Table 166.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.13	0.03	0.03	0.87	0.04
<b>NO-GRID - Mean</b>	0.05	1.82	0.26	0.01	2.09	0.02
<b>GRID - Median</b>	0.04	0	0.02	0.02	0	0.03
<b>NO-GRID - Median</b>	0.04	0	0	0.01	0	0.02
<b>GRID - Variance</b>	0	0.54	0	0	5.94	0
<b>NO-GRID - Variance</b>	0	8.17	2.23	0	10.62	0

**Table 167.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.309	0.02	0.23	0.24	0	0.2
<b>NO-GRID - Mean</b>	0.557	0.01	0.04	0.19	0	0.2

**Table 168.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.051	0	0.04	0.04	0	0.03	0.84
<b>NO-GRID - Mean</b>	0.052	0	0	0.02	0	0.02	0.91

## Grass – Södermanland damage types ratios

### Grass - Object-based Random Forest Damage Classification

**Table 169.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the grass fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	674233m <sup>2</sup>	7023m <sup>2</sup>	6308m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 170.** The ratio between the total area of predicted damage (by classification 1, Object-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.42</b>	0.3	0.76

**Table 171.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.04	0.12	0.12	0.05	0.51
<b>NO-GRID - Mean</b>	0.13	0.04	0.02	0.08	0.26	0.72
<b>GRID - Median</b>	0.14	0.01	0.1	0.1	0.03	0.52
<b>NO-GRID - Median</b>	0.09	0.02	0.01	0.06	0	0.76
<b>GRID - Variance</b>	0.01	0.01	0.01	0.01	0	0.03
<b>NO-GRID - Variance</b>	0.02	0	0	0.01	2.15	0.03

**Table 172.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.05	0.05	0.05	0.04	0.01	0.22
<b>NO-GRID - Mean</b>	0.04	0.18	0.29	0.03	1.04	0.22
<b>GRID - Median</b>	0.04	0	0.02	0.03	0.01	0.14
<b>NO-GRID - Median</b>	0.02	0	0	0.01	0	0.15
<b>GRID - Variance</b>	0	0.18	0.02	0.01	0	0.28
<b>NO-GRID - Variance</b>	0	1.48	1.89	0.01	5.49	0.23

**Table 173.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.151	0.03	0.11	0.12	0.04	0.54
<b>NO-GRID - Mean</b>	0.149	0.03	0.03	0.09	0	0.7

**Table 174.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.035	0.01	0.03	0.03	0.01	0.13	0.77
<b>NO-GRID - Mean</b>	0.027	0.01	0	0.02	0	0.13	0.82

## Grass - Object-based Support Vector Machine Damage Classification

**Table 175.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the grass fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	601624m <sup>2</sup>	6267m <sup>2</sup>	5900m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 176.** The ratio between the total area of predicted damage (by classification 1, Object-based Support Vector Machine) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.35</b>	0.28	0.23

**Table 177.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.16	0.04	0.11	0.12	0.05	0.52
<b>NO-GRID - Mean</b>	0.15	0.07	0.03	0.09	0.31	0.68
<b>GRID - Median</b>	0.13	0.01	0.09	0.1	0.03	0.53
<b>NO-GRID - Median</b>	0.12	0.03	0	0.06	0	0.71
<b>GRID - Variance</b>	0.01	0.01	0.01	0.01	0	0.03
<b>NO-GRID - Variance</b>	0.02	0.06	0	0.01	2.16	0.03

**Table 178.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.04	0.15	0.04	0.04	0.01	0.17
<b>NO-GRID - Mean</b>	0.04	0.02	0.53	0.02	0.99	0.17
<b>GRID - Median</b>	0.03	0	0.02	0.02	0.01	0.13
<b>NO-GRID - Median</b>	0.02	0	0	0.01	0	0.12
<b>GRID - Variance</b>	0	1.01	0	0	0	0.07
<b>NO-GRID - Variance</b>	0	0.02	3.72	0	4.62	0.04

**Table 179.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.148	0.03	0.11	0.12	0.04	0.55
<b>NO-GRID - Mean</b>	0.163	0.04	0.03	0.08	0	0.68

**Table 180.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.031	0.01	0.02	0.03	0.01	0.11	0.79
<b>NO-GRID - Mean</b>	0.027	0.01	0	0.01	0	0.11	0.84

## Grass – Pixel-based Random Forest Damage Classification

**Table 181.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the grass fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
<b>96</b>	469328m <sup>2</sup>	4889m <sup>2</sup>	5963m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 182.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
<b>0.24</b>	0.18	0.12

**Table 183.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.09	0.12	0.12	0.05	0.52
<b>NO-GRID - Mean</b>	0.21	0.12	0.11	0.17	0.01	0.54
<b>GRID - Median</b>	0.12	0.01	0.1	0.09	0.03	0.53
<b>NO-GRID - Median</b>	0.19	0.02	0	0.16	0.01	0.55
<b>GRID - Variance</b>	0.01	0.25	0.01	0.01	0	0.03
<b>NO-GRID - Variance</b>	0.02	0.68	0.65	0.01	0	0.02

**Table 184.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.38	0.03	0.02	0.01	0.13
<b>NO-GRID - Mean</b>	0.03	0.16	0.5	0.03	0.43	0.09
<b>GRID - Median</b>	0.02	0	0.01	0.01	0	0.09
<b>NO-GRID - Median</b>	0.02	0	0	0.02	0	0.06
<b>GRID - Variance</b>	0	2.72	0	0	0	0.05
<b>NO-GRID - Variance</b>	0	1.26	3.05	0	2.38	0.02

**Table 185.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.145	0.03	0.13	0.12	0.04	0.54
<b>NO-GRID - Mean</b>	0.244	0.03	0.08	0.14	0.01	0.49

**Table 186.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.023	0	0.02	0.02	0.01	0.09	0.84
<b>NO-GRID - Mean</b>	0.028	0	0.01	0.02	0	0.06	0.88

## Grass - Pixel-based Support Vector Machine Damage Classification

**Table 187.** The total fields predicted in Södermanland, together with the total area, and mean and standard deviation of the grass fields in Södermanland, of the predicted damage and field area.

<b>Total Field Predicted</b>	<b>Damage Area Total</b>	<b>Damage Area Mean</b>	<b>Damage Area Standard Deviation</b>	<b>Field Area Total</b>	<b>Field Area Mean</b>	<b>Field Area Standard Deviation</b>
96	486479m <sup>2</sup>	5067m <sup>2</sup>	7764m <sup>2</sup>	2906963m <sup>2</sup>	30281m <sup>2</sup>	33128m <sup>2</sup>

**Table 188.** The ratio between the total area of predicted damage (by classification 1, Pixel-based Random Forest) and the total area of the fields in the Södermanland study area.

<b>Ratio Damage vs Field Area Mean</b>	<b>Ratio Damage vs Field Area Median</b>	<b>Ratio Damage vs Field Area Variance</b>
0.23	0.17	0.06

**Table 189.** The ratio between the total area of the specific damage type predicted and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damage</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.15	0.04	0.12	0.12	0.04	0.54
<b>NO-GRID - Mean</b>	0.21	0.06	0.03	0.15	0.15	0.57
<b>GRID - Median</b>	0.13	0.01	0.1	0.09	0.03	0.54
<b>NO-GRID - Median</b>	0.17	0.02	0	0.14	0.01	0.57
<b>GRID - Variance</b>	0.01	0	0.01	0.01	0	0.04
<b>NO-GRID - Variance</b>	0.03	0.14	0.01	0.01	0.9	0.04

**Table 190.** The ratio between the total area of the specific damage type predicted and the total area of the wheat field.

<b>Ratio</b>						
<b>Field Area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.03	0.5	0.13	0.02	0.07	0.12
<b>NO-GRID - Mean</b>	0.03	0.23	0.4	0.02	0.27	0.09
<b>GRID - Median</b>	0.02	0	0.01	0.01	0	0.09
<b>NO-GRID - Median</b>	0.01	0	0	0.01	0	0.05
<b>GRID - Variance</b>	0	3.41	0.93	0	0.37	0.03
<b>NO-GRID - Variance</b>	0	1.8	2.19	0	1.58	0.01

**Table 191.** The ratio between the total area of the predicted specific damage type and the total area of predicted damage.

<b>Ratio</b>						
<b>Predicted damages</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>
<b>GRID - Mean</b>	0.137	0.03	0.13	0.11	0.03	0.57
<b>NO-GRID - Mean</b>	0.269	0.02	0.06	0.11	0.01	0.53

**Table 192.** The ratio between the total area of the predicted specific damage type and the total area of all the fields.

<b>Ratio</b>							
<b>Total field area</b>	<b>Wild boar</b>	<b>Deer</b>	<b>Drought</b>	<b>Machine</b>	<b>Stone</b>	<b>Water</b>	<b>No damage</b>
<b>GRID - Mean</b>	0.023	0	0.02	0.02	0.01	0.09	0.83
<b>NO-GRID - Mean</b>	0.033	0	0.01	0.01	0	0.06	0.88