Unsupervised remote sensing analysis of long-term land-use and land cover dynamics of European Green Toad (*Bufotes viridis)* habitats in southern Sweden

Using an unsupervised remote sensing method in combination with post-processing and manual correction to compare 1950s habitat composition of extant and extinct *B. viridis* habitats to the 2010s.

Nordens Ark

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SUMMARY

Nowadays, the European green toad (*Bufotes viridis*) is Sweden's most threatened amphibian species due to habitat loss and fragmentation, disease and anthropogenic influences. This study focused on habitat composition differences and changes in *B. viridis* habitats in the 1950s and 2010s to determine if this could have contributed to the species' decline. In addition, this study investigated whether extant and extinct habitats differed in degree of habitat openness and if the openness changed between the 1950s and the 2010s. The comparison was made by remote sensing and classification of, in 2022, seven extant and seven extinct habitats. The classifications were done on historical panchromatic (1956-1967) and modern infrared aeroplane imagery (2008-2016) using the ISO-cluster unsupervised classifier in combination with post-processing and manual correction. The method was evaluated on its performance in terms of accuracy to determine if it suits the needs of Nordens Ark.

The results show significant habitat composition differences between extant and extinct *B. viridis* habitats in the 1950s and the 2010s. Extinct habitats contained much more agriculture and much less barren land in the 1950s and 2010s. The combination of these habitat stressors could have contributed to decreasing *B. viridis* populations through reducing habitat sizes, habitat fragmentation, and increased migration. Furthermore, these adverse area characteristics were present in extinct habitats before the 1950s, indicating that the critical thresholds for barren land and agriculture were exceeded long ago and that the decrease of the *B. viridis* population in Sweden was a delayed and slow event. However, habitat openness is unlikely to have contributed to the decline of *B. viridis* because no differences regarding habitat openness were found.

The remote sensing method of this study shows promising results and highlights the necessity of unsupervised classification in combination with high-resolution imagery, post-processing and manual correction. However, the probability that features in the field are classified correctly due to chance is slightly higher than preferred. Thus, familiarity with the target habitats is essential to reduce the possible inaccuracies due to human interpretation and manual correction. Nevertheless, it produces maps that represent features in the field satisfactorily.

Further conservation efforts should focus on habitats with much barren land and little agriculture. Furthermore, terrestrial habitats could be protected by implementing landscape-scale protection guidelines in the *B. viridis* species action plan. In addition, new habitats can be created to reduce the effects of habitat isolation, habitat fragmentation and mortality due to migration.

When using remote sensing for animal conservation, it is recommended to use imagery with a high pixel detail and to familiarise oneself with the target habitat to reduce inaccuracies in the created classification map. Furthermore, it is recommended to classify urban and similar areas as a whole and not by their components, such as roads, gardens and houses.

In conclusion, remote sensing shows the potential to strengthen the conservation strategy of Nordens Ark and can be used to identify suitable reintroduction sites and habitats for *B. viridis*.

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1 INTRODUCTION

1.1 BACKGROUND INFORMATION

Bufotes viridis. The European green toad (*Bufotes viridis*), **Error! Reference source not found.**, can be found in most of Europe, parts of Central Asia and North Africa. Southern Scandinavia, the Baltic states, and Russia are the northernmost boundary where *B. viridis* can be found[1]–[4].

B. viridis is a predominantly terrestrial species spending most of its life on firm and dry ground. In Sweden, *B. viridis* prefers to live in open habitats consisting of shoreline meadows and shallow water bodies surrounded by shrubs and low grasses, which are quickly warmed up in early spring and summer. Terrestrial habitats are essential as the primary living habitat, and wetlands for breeding[2][5]. When these shallow bodies of water warm up, the water also provides juvenile toads with a food source[2]. Nordens Ark tracked 17 released *B. viridis* in Högby hamn, Öland, using radio telemetry in September 2020. While tracking, there were indications that the species prefers open habitat types while avoiding areas with trees, tall grass, or both (pers. obs. unpublished data, K. Försäter, S. Qualm, 2020).

Figure 1, Bufotes viridis

In recent decades human activity has caused changes to biodiversity. The habitats of *B. viridis* are reduced by anthropogenic and natural activities such as land-use change and possibly a decrease in grazing [7]. In addition, agriculture, lowering water levels, predation, and disease affected the toad and its habitats [2], resulting in more homogeneous landscapes, habitat loss, fragmentation, and degradation. The consequences of habitat loss are dwindling population sizes and reduced ecosystem and genetic diversity[8]. However, climate change has been estimated to be a less likely driver of Sweden's *B. viridis* population decrease [9]. Genetic diversity is required for species to adapt to changes. Without it, the toad species is prone to reduced gene flow and local extinction [10]. Because of this, *B. viridis* is known as “the most vulnerable amphibian species in Sweden” [8]. Unfortunately, analyses show that human activities and land use keep intensifying at the cost of the environment[11].

Since the 1930s, grasslands in southern Sweden have made way for spruce plantations and industrialised agriculture, particularly crop production [12]. Nowadays, *B. viridis'* terrestrial and aquatic habitats are threatened. As a result, the County Administrative Board of Kalmar intensified the conservation efforts of *B. viridis* through habitat restoration and reintroduction in collaboration with Nordens Ark in 2009. Since then, the county board has restored coastal habitats on the island of Öland. In addition, tadpoles, juveniles and adult toads have been released by Nordens Ark in a bird sanctuary named Högby hamn in the northern part of Öland. Högby hamn was chosen as the reintroduction site because *B. viridis* was last found on the island's northern part before it was listed as locally extinct in this region[2], [3].

Remote sensing. Habitat changes have become easier to monitor since the emergence of satellite imagery in the 1970s. Remote sensing can be used to monitor areas from a distance by using electromagnetic multispectral drone, aeroplane or satellite images. Using Geographical Information System (GIS) software, the multispectral images are analysed on their spectral properties to classify the area with respect to land use and vegetation types. In remote sensing, GIS classifications will result in different Land Use and Land Cover (LULC) classes. Examples of classes are urban, roads, concrete, trees, grass, sand, etc. By classifying a time series of a specific area, information about LULC change can be acquired, and trends identified [13].

Combining ground data and remote sensing is a valuable method for identifying area characteristics. Before remote sensing was a commonly used tool, it was exclusively required for one to be in the field to gather information about the monitored area. Whereas with remote sensing, this is not necessarily the case. However, methods requiring one to be *in situ* are not easily applicable on a large scale and are too labour intensive and time-consuming. While *in situ* methods could be more accurate and provide a vast amount of information, it is preferred to use remote sensing in combination with low-intensity ground-truthing as it is applicable on a large scale and can be used for prediction and quantification [13].

Nordens Ark. The organisation Nordens Ark is a private non-profit foundation that aims to conserve endangered animals through breeding, research, education and training. Endangered animals reared at Nordens Ark are reintroduced into the wild, often combined with habitat restoration in collaboration with the Swedish environmental agency Naturvårdsverket and the various Swedish county boards.

Since the early 2000s, Nordens Ark has reintroduced thousands of animals born at the zoo [14]. One of the released species is the European green toad. By remote sensing LULC changes in extinct and extant *B. viridis* habitats, Nordens Ark hopes to find a possible cause of the *B. viridis* population decline and possibly guide future research. Furthermore, this may identify what improvements can be made to its habitats so that future restoration efforts will be more effective because limited adult toads have been observed in Högby hamn since the increased conservation efforts in 2009.

1.2 GOAL

Through remote sensing, this project aimed to determine if there are habitat differences between extant and extinct B. *viridis* habitats that could have contributed to the decline of this species in Sweden. This was done by comparing seven extinct habitats (no toads present in 2022) to seven extant habitats (toads present in 2022). In addition, the habitat composition of extant and extinct habitats in the 1950s was compared to the 2010s to determine if there was a significant change over time. The habitat classifications were performed on historical panchromatic (grey-scale) aeroplane imagery (1956-1967) and modern infrared aeroplane imagery (2008-2016).

1.3 HYPOTHESIS

It is hypothesised that extant habitats and extinct *B. viridis* habitats significantly differ in habitat composition. In addition, *B. viridis'* population declined due to habitat changes such as the conversion of grasslands to forests and agriculture and, for *B. viridis*, unfavourable vegetation growth, changing the composition in its habitats from open to covered in the last six decades. Furthermore, remote sensing of habitats could be an easily applicable method for Nordens Ark to help reintroduce animals. The hypothesis leads to the following research questions:

1. Did the habitat openness of *B. viridis* habitats change significantly in the last six decades, possibly contributing to the decline of the population size of the toad species in Sweden?
2. Is there a significant difference in habitat composition between extant and extinct *B. viridis* habitats?
3. How much has the habitat composition of *B. viridis* habitats changed between the 1950s and the 2010s, and could that change have led to the decline of Sweden's *B. viridis* population?
4. Is unsupervised classification in combination with post-processing and manual correction suitable for the needs of Nordens Ark?

1.4 READING GUIDE

The second chapter gives a theoretical background. It presents relevant literature and information about several topics related to this study. Firstly, the habitat preferences of *B. viridis* are reviewed, and the habitat preferences and threats are substantiated. Secondly, several remote sensing techniques are explained, their benefits and drawbacks, and what steps could be taken to improve the accuracy of the created classification map. Finally, some accuracy assessment methods are listed and how to interpret their assessment results. The third chapter presents the overall methodological approach used in this study and substantiates the individual steps. The results in the fourth chapter list the findings of this study and provide their implications. Subsequently, the findings and method are discussed and compared to similar studies. Finally, the conclusions are presented which are followed by the recommendations.

2 THEORETICAL BACKGROUND

This chapter presents relevant literature and information about several topics related to this study. Firstly, the habitat preferences of *B. viridis* are reviewed, and the habitat preferences and threats are substantiated. Secondly, several remote sensing techniques are explained, their benefits and drawbacks, and what steps could be taken to improve the accuracy of the created classification map. Finally, some accuracy assessment methods are listed. The methods are explained, what sampling methods there are and how to interpret the accuracy assessment results.

2.1 *BUFOTES VIRIDIS* HABITAT

B. viridis is globally listed as "least concern" by the IUCN. It is a relatively common toad species in Europe; it occurs from eastern France to southern Scandinavia, northern Africa and Central Asia [1]. However, its population trend is declining and red-listed in Sweden [5]. The toad is able to live in steppes, is adapted to dry, arid environments and prefers open habitat types with low scattered vegetation and woody debris that provide a place for thermoregulation and predator avoidance [15]–[18]. It can be found in agricultural environments with warm climates and lives close to humans, which it might even benefit from[19]. In urban environments, city parks, ponds, gardens, and ruderal lands make suitable habitats [20]–[22]. However, if habitats are disturbed too much, toads will migrate further in search of nutrients or more suitable habitats [18].

Despite human activity being described as one of the pressures by the IUCN [5], *B. viridis* was discovered in Vienna's urban environment by Josephus Nicolaus Laurenti in 1768. The toad was found in the shadow-rich crevices of the city walls [23]. However, it has been suggested that terrestrial habitat quality is affected by intensive human land use and that *B. viridis* life-history traits (age at maturity, size at maturity, longevity, reproductive lifespan and age-size relationship) are linked to its habitat quality. The affected traits confirm the life-history theory, meaning that toads living near environments with intense human land use mature earlier but are smaller and have shorter lifespans [24].

The IUCN states that the primary pressure on *B. viridis* is the disappearance of breeding habitats. The decline of suitable breeding habitats is caused by wetland drainage, droughts, and pollution by agriculture and industry [25]–[28]. Sweden implemented sustainable agriculture and rural development frameworks in 1997. The implemented framework mainly focused on stabilising nitrate levels in water supplies. But it also limited the quantity of fertilizer and livestock manure that could be applied to fields. In addition, rules were established on record keeping, waste handling, and storage facilities [29]. Despite implementing frameworks that promote sustainable agriculture, Sweden still employed unsustainable agricultural practices in 2004 [30]. In southern Sweden, agriculture uses vast amounts of nitrogen, phosphorus, and synthetic pesticides, leading to disturbed nutrient cycles and environmental pollution and thus decreasing the number of suitable habitats [30], [31]. In addition, toads are at risk of dying when crossing roads during migration[5], [32].

In summary, *B. viridis* prefers open habitat types and is not necessarily negatively affected by urban environments. However, intensive human land use, such as agriculture, causes the decline of *B.viridis* populations due to the loss of suitable habitats. In addition, if habitat quality is insufficient due to human activities or the lack of landscape elements (e.g., woody debris and stone walls) that offer protection and a place for thermoregulation, toads mature and die earlier [24].

2.2 IMAGE CLASSIFICATION.

For effective land management, it is useful to identify LULC changes over a period of time so that their dynamics are identified [13], [33]. Image classification of historical panchromatic aeroplane photography is a valuable method to identify these changes as they have a longer history than satellite imagery. Because of this, such imagery offers the potential for detailed ecological assessments[34].

Using Machine Learning (ML) for classifying LULC of areas substantially reduces human labour and costs compared to manual classification methods. ML uses algorithms to teach classifiers to identify what LULC classes are represented by specific multispectral information and creates classes based on this information. Nowadays, there are two different classifier types for ML classification: Unsupervised Machine Learning (UML) and Supervised Machine Learning (SML) (Table 1). Both SML and UML can produce satisfactory results when classifying panchromatic and modern imagery, but SML generally achieves better accuracy[35], [36].

SML and UML classifiers can be subdivided into pixel and object-based classifiers. Pixel-based classifiers analyse the spectral properties of individual pixels without taking spatial or contextual features into account, resulting in noise or a so-called "salt and pepper" effect [37], [38]. On the other hand, object-based classifiers consider those features by grouping pixels together using segmentation. However, this makes the method prone to over or under-segmentation. Over-segmentation causes inaccuracies by grouping too many pixels together, resulting in a too coarse classification map. In contrast, under-segmentation could result in the exclusion of spatial and contextual features, thus also impacting classification accuracy [39].

Some classifiers are easier to use than others. Support Vector Machine (SVM), Maximum likelihood classification (MLC), Artificial Neural Network (ANN) and Object-Based Imagery Analysis (OBIA) require the user to provide training samples to the classifier, while Decision Trees (DT) requires the setup of elaborate decision trees for the classification. These 5 SML classifiers require the user to assign values to pixels or objects, increasing human labour. In addition, advanced knowledge about the use of these classifiers is practically mandatory in order to achieve good accuracy values and thus create reliable classification maps. On the other hand, ISO-cluster Unsupervised Classification (ICUC) and K-MEANS only require the user to provide the wanted number of classes to be specified, increasing processing speed but possibly at the cost of accuracy [40]. However, a proper comparison of classifiers is still absent, making it difficult to state which is better [41].

Table 1, contemporary image classification classifiers.

SML	UML
Support Vector Machine (SVM) (pixel)	ISO-cluster unsupervised classification (ICUC) (pixel)
Maximum likelihood classification (MLC) (pixel)	K-MEANS (object)
Artificial neural network (ANN) (pixel)	
Decision trees (DT) (pixel)	
Object-based imagery analysis (OBIA) (object)	

A challenge of historical image classification is that such imagery often is panchromatic (grey-scale). Therefore, pixels of classes can share similar spectral properties due to a lack of pixel information (e.g. water looks black and could look like roofs) [42]. Pre-processing of the imagery might be required to alleviate the lack of pixel information. Segmentation of the imagery could introduce additional information by producing more homogeneous regions, allowing for a better distinction of objects and spectral properties [43]. Pre-processing of panchromatic imagery can also focus on contrast correction to make classes more distinguishable. These corrections can be done in software like GNU Image Manipulation Program (GIMP) or Adobe Photoshop [44], but also in GIS software.

2.3 ACCURACY ASSESSMENT

After classifying, the classification map needs to be assessed on its accuracy, or rather how well it reflects reality. An accuracy assessment is necessary because the efficacy of LULC maps relies on knowing its uncertainty [45]. Transparency of accuracy assessment methods is essential for the integrity and reliability of LULC information [46].

Unfortunately, less than a third (32%) of remote sensing studies used replicable accuracy assessment methods, making comparisons to other studies challenging. It is most common to report the Overall Accuracy (OA), Kappa Coefficient (KC), User Accuracy (UA) and Producer's Accuracy (PA) when describing the accuracy of a created classification map [45]. Confusion matrices of the samples can be created to measure the agreement between classification and reality. The matrices are based on points of the created classification maps that have been compared to higher accuracy maps or imagery of which the user is 100% certain that these points/polygons represent a specific LULC in reality. Confusion matrices show information about actual and predicted classifications and provide the following information [47]:

1. Overall Accuracy (OA): is the total accuracy percentage of a map based on the producer accuracy of all classes. OA does not consider the accuracy of individual classes.
2. Producer Accuracy (PA): this value shows the probability that a certain feature of an area in the field is correctly classified. *For example, the LULC class "trees" achieved 45% PA, meaning that 45% of actual trees are correctly classified.*
3. User Accuracy (UA): this value shows the probability that a pixel labelled as a certain class is actually that class in reality. *For example, the LULC class "grass" achieved 75% UA that there is a 75% chance that an area classified as "grass" is actually grass in the field.*
4. Kappa Coefficient (KC): this value shows how well the classification represents reality due to change only and is often presented as a percentage. Where 100% KC shows perfect agreement between the created classification maps and reality, and -100% shows no agreement with reality at all. KC provides a better interclass distinction than OA. *For example, a classification map with 81 % KC. So, when the map is used, there is a 19% probability that features in the field are correctly classified only due to chance.*

Generally, a classification is deemed acceptable if the KC and OA are above 85% [48][49]. However, raising or lowering this value might be a good practice depending on the spectral properties of classes. Increasing the minimum accuracy value is a good practice if classes are spectrally distinct. On the other hand, if classes are not as spectrally separable, it might be better to lower the minimum accuracy value [49].

It is entirely possible that the OA and KC of a classification map show good results. However, while those values are high, the UA and PA of (some) individual classes could be low, while others could be high. Meaning, that if the finished classification map were to be used, the user would encounter a different LULC class than indicated on the map. Therefore, consideration should also be given to the UA and PA when reporting the accuracy of a classification map and when specific LULC classes are of interest to the user [50].

Several sampling types are commonly used when determining the accuracy of a classification map; all methods provide the user with sampling data for the accuracy assessment. The sampling data can be compared to more accurate classification maps or higher resolution photos to determine the classification accuracy. This comparison assesses the sampling data to determine whether a sampling point is correctly classified or mistaken for another LULC class. In order of most to least prevalent sampling types [29]:

- Pixel: a single pixel from higher or similar resolution imagery is compared to the created classification map.
- Pixel cluster: a group of pixels from higher or similar resolution imagery is compared to the created classification map.
- Polygons: an irregular amount and shaped group of pixels from higher or similar resolution imagery is compared to the created classification map.
- Field plots: samples gathered in the field using an area-based sampling unit. The collected field data will be compared to the created classification map.
- GPS-points: point feature data collected from a GPS device. The points can be used to ground-truth the created classification map.
- Map correlation: Comparison with a map that is more accurate.

Despite pixel sampling gathering being used most often, it does not imply that it is the best accuracy assessment method. For example, an area within the classification map can be assessed on its accuracy to determine the accuracy of the whole map. The assessment can be done by comparing the classification map to the originally used aeroplane photos [51].

3 METHODOLOGY

Overall approach. This study started with gathering information about the location of *B. viridis* habitats in Sweden, which can be challenging when not proficient in Swedish. Fortunately, Ballard-Johansson [9] compiled a list of all *B. viridis* habitats (and habitat coordinates), making the study area selection process much more manageable. Seven extant and seven extinct habitats were selected to make a fair comparison. In the 1950s, none of the used habitats was extinct. However, the terms extant and extinct are still used when describing the habitats in the 1950s because the terms are based on the state of the habitats in 2022. Subsequently, literature was studied about the remote sensing methods and habitat preferences of *B. viridis* so that when the study areas were visited, it was known what Land Use and Land Cover (LULC) to look for when in the field. In this period, the aeroplane imagery of habitats was gathered, and some classification classifiers were tested to determine which classifier was most suitable for this study. After the literature study, the study areas were visited to gather information about their geography and LULC for referencing during the classification process. After returning from the study area visits, the classification process began. This included pre-processing (when necessary), the image classification, post-processing, and manual correction. The last step in the classification process is the accuracy assessment. A flowchart, Figure 3, was created to provide an overview of the classification process. Finally, an analysis of the results was done in which the habitat composition differences of extant and extinct habitats were compared.

Selection of study areas. This study focused on 14 *B. viridis* habitats (Figure 2) in southern Sweden (Appendix A – European green toad habitats). The choice of the number of study areas was based on the number of extant habitats and how laboursome and time-consuming the classification process could be. Since there are only seven extant habitats in 2022, it was chosen to use the seven most recently extinct habitats (last observation between 2007 and 2010) of past *B. viridis* occurrence so that a fair comparison could be made. The choice to use the most recently extinct habitats was based on the assumption that there was a higher chance of finding the cause for the *B.viridis* population decrease due to their relatively recent state of extinction.

The centre of habitats was the longitude and latitude, based on the study of Ballard-Johansson [9]. A polygon with a radius of 1km from the observation location was created in ArcGIS Pro and used as the study area, making the surface area per habitat 3,14 km^2. If the polygon area contained a significant amount of water (based on visual observation of the aeroplane imagery), the centre of the study area was moved to include more terrestrial LULC while remaining as close as possible to the original location. If an extinct habitat was closer than 1km to a

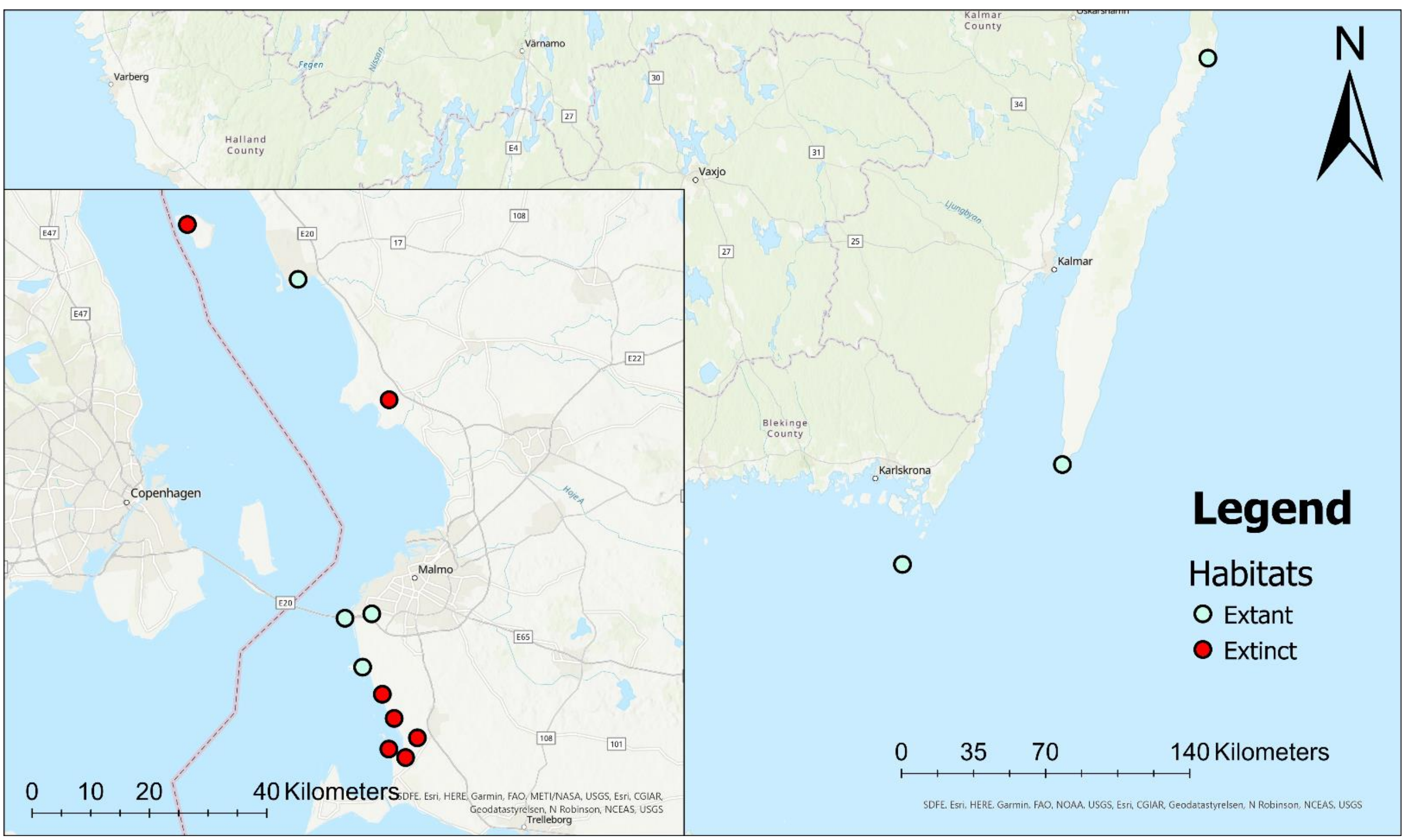

Figure 2, the habitats used in this study.

different studied habitat, it was excluded from the study, and the next most recently extinct habitat was used. This was done so that there was no overlap of study areas.

Study area visits. All habitats (Appendix A) except Utklippan and Ven and Ven were visited to familiarise oneself with their LULC. During these visits, photos and notes were taken of the landscape: E.g. vegetation height and density. The gathered information proved to be helpful for referencing in the classification process.

Image classification. The imagery for the classifications was obtained from Landmäteriet. The historical aeroplane imagery was orthorectified (conversion of raw photography by removing sensor and aircraft motion and terrain-related distortions) panchromatic with a pixel detail of 0.5m and 8bit colour depth and ranged from 1956 to 1965. The modern aeroplane imagery was orthorectified infrared with a pixel detail of 0.5m and 24bit colour depth, ranging from 2008 to 2016. The imagery dates are unknown, but Landmäteriet states they were taken in autumn. Because of that, there was a notable difference in visible water in wetlands and ponds in the imagery due to the wet season (autumn/winter). Because there was only one year available of historical panchromatic imagery and multiple years of modern infrared imagery, it was chosen to match the amount of visible water in modern infrared imagery to what was visible in the historical panchromatic imagery.

All panchromatic imagery required pre-processing to increase contrast and detail; this was done by increasing the colour depth to 32bit signed in ArcGIS Pro 2.9+. If multiple images covered a habitat, they were merged by creating a new mosaic, Figure 3.

Initial testing of SML (SVM) and UML (ICUC) classifiers was done to determine which would be best suited. The choice for these classifiers was based on personal knowledge of how to use these. In addition, SVM was chosen over MLC because literature showed that it generally achieved better accuracy when classifying panchromatic imagery. The testing showed that both classifiers required substantial amounts of manual correction. However, SML was more laboursome due to the required training with training data in ArcGIS. Therefore, due to time constraints, the ICUC algorithm classifier was used for the image classifications of both historical panchromatic and modern infrared imagery. Post-processing was done to clean up the classified maps and reduce noise (the so-called "salt and pepper" effect) by using the majority filter and boundary clean-up. By doing this, the classified "noisy" pixels are converted to another class that surrounds the "noisy" pixels.

Manual correction. After post-processing the classification maps, manual correction had to be performed. The first correction step was done by converting the raster files to polygons and assigning numbers to the LULC classes. Then, the number of wrongly classified polygons was changed to the correct corresponding LULC class number. Occasionally, the shape of polygons had to be modified by cutting it to the correct shape. Correction priority was given to large polygons. However, if a LULC class (e.g. structures) had a relatively low surface area compared to other LULC classes (e.g. "agriculture"), corrections were done with as much detail as possible.

Normalisation. Because each classification had unique LULC classes, they needed to be normalised before a comparison could be made. In addition, the normalised classes were classed to be an open or covered LULC type, Table 2 and Figure 3.

Table 2, normalisation system for the LULC classes used in this study.

Normalised LULC class	Open/covered	Associated LULC class
Agriculture	Open	• Agriculture (crop fields)
Barren	Open	• Bare mineral soil • Barren mineral surface with scattered shrubs and small bushes • Rocks and stones
Forest	Covered	• Bushes and trees
Herbaceous	Open	• Grass
Urban	Covered	• Structures • Railroads • Roads • Industrial products and bulk storage • Sealed concrete & stone surfaces • Sealed concrete and asphalt surfaces • Wall
Wetland	Open	• Wetland with long grass • Wetland with reeds • Temporary pool
Water	Open	• Water

Accuracy assessment. To assess the accuracy of the created classification maps, accuracy assessments have been performed on five randomly selected habitats (Appendix A – European green toad habitats). One hundred stratified random points were assessed for these five habitats by comparing them to the used historical aeroplane and the modern infrared aeroplane images. Unfortunately, this method makes the accuracy assessment of the panchromatic imagery prone to misinterpretation and thus a likelihood of inaccuracy. Subsequently, confusion matrices were created based on these points, Figure 3. It should be noted that ArcGIS might create more, but never less than the specified amount of ground-truthing points.

Analysis. Comparisons of extant and extinct habitats were made to determine if the two states had significant differences in LULC in the open-source statistical program Jamovi. The first analysis is based on the Modern Infrared Aeroplane Imagery (MIAI) classification and was used to determine if there was a significant difference in one or more LULC classes in the 2010s when comparing extant and extinct habitats. The second analysis is similar to the first and was used to determine if there is a significant difference between extant and extinct habitats in the 1950s of one or more LULC classes based on the Historical Panchromatic Aeroplane Imagery (HPAI) classifications. The third analysis determines if LULC classes of only extant habitats have changed significantly between the 1950s and 2010s. The fourth and final analysis is similar to the third. However, it is used to determine if the LULC of only extinct habitats has changed significantly between the 1950s and 2010s.

The analyses were done by comparing the normalised LULC classes using independent samples T-tests. T-tests were chosen because, at all times, only two means were compared to look for specific relationships (e.g., the mean of the LULC class forest of extant habitats is compared to the mean of extinct habitats. Or, water of extant habitats in the 1950s is compared to water of extant habitats in the 2010s). Depending on what assumptions were violated, different t-tests were used. A violation of an assumption occurs when $p \leq 0.05$

- If no assumptions were violated, a Student's t-test was used.
- If the normality test was violated, but the homogeneity of variance was not, a Mann-Whitney-U t-test was used.
- If the normality test was unviolated, but the homogeneity of variance was violated, a Welch's t-test was used.
- A Mann-Whitney-U t-test was used when both assumption checks were violated.

Two hypotheses are presented to determine if a t-test is significant, meaning that there is a significant difference between two means of the same LULC class:

1. H_0: there is no significant difference between the two means; $p > 0.05$.
2. H_a: there is a significant difference between the two means; $p \leq 0.05$.

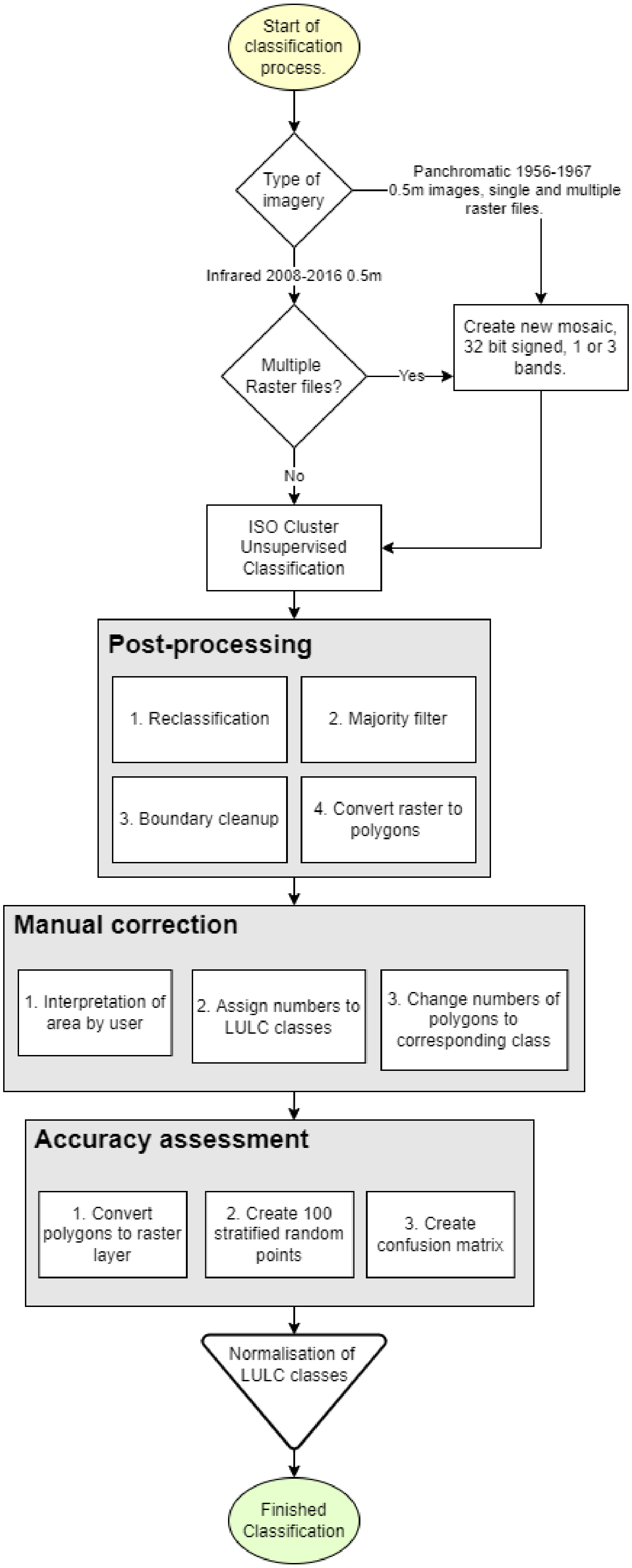

Figure 3, flowchart of the classification process.

4 RESULTS

This chapter aims to present how LULC of extant and extinct habitats differ from each other. Moreover, to identify if the LULC of extant habitats and extinct habitats has changed significantly over time. This was done by classifying seven extant and seven extinct habitats using Historical Panchromatic Aeroplane Imagery (HPAI, 1956-1967) and Modern Infrared Aeroplane Imagery (MIAI, 2008-2016).

In the 1950s, none of the used habitats was extinct. However, the terms extant and extinct are still used when describing the habitats in the 1950s because the terms are based on the state of the habitats in 2022. The first and second analyses determine if the LULC of extant habitats differs from extinct habitats, in the 1950s and 2010s, respectively. Comparing LULC between extant and extinct habitats identifies possible habitat differences that might have contributed to the decline of *B. viridis* (e.g., a significant difference between open LULC and covered LULC). The third and fourth analyses look at extant habitats and extinct habitats separately to determine if the LULC of either habitat state changed significantly over time, from the 1950s to the 2010s. This analysis is important because it shows if the LULC of extant or extinct habitats changed after the 1950s or if little change occurred. Thus, showing that the decline *B. viridis'* population was possibly already happening due to the adverse habitat conditions before the 1950s.

4.1 LAND USE AND LAND COVER

4.1.1 Comparing extant habitats to extinct habitats.

In this analysis, "p" indicates how likely it is that there is a significant ($p \leq 0.05$) difference between extant habitats and extinct habitats at one point in time. The analysis shows that extinct habitats have significantly more "agriculture" than extant habitats in the 1950s ($p = 0.02$, 8.87km2 & 1.16km^2) and the 2010s ($p = 0.039$, 6.58 km^2 & 0.4km^2). Extant habitats had 87% less "agriculture" in the 1950s and 94% less in the 2010s than extinct habitats, Table 3, Figure 4 and Appendix B – The sum of square kilometres per LULC.

Extinct habitats have significantly less "barren" LULC than extant habitats in the 1950s ($p = 0.21$, 0.55 km^2 & 3.98km^2) and the 2010s ($p = 0.005$, 0.28km^2 & 3.13km^2). Extinct habitats had 86% less "barren" land than extant habitats in the 1950s and 91% less in the 2010s, Table 3, Figure 4 and Appendix B – The sum of square kilometres per LULC.

There was no significant difference of open LULC and covered LULC when comparing extant habitats to extinct habitats, making it unlikely that the difference in habitat openness contributed to the decline of *B. viridis*.

Table 3, t-tests comparing LULC classes of extinct and extant habitats in MIAI and HPAI.

LULC Class	HPAI p	MIAI p
Agriculture	0.020	0.039
Barren	0.021	0.005
Forest	0.522	0.805
Herbaceous	0.935	0.311
Urban	0.463	0.902
Wetland	0.855	0.794
Water	0.096	0.160
Open	0.442	0.584
Covered	0.456	0.902

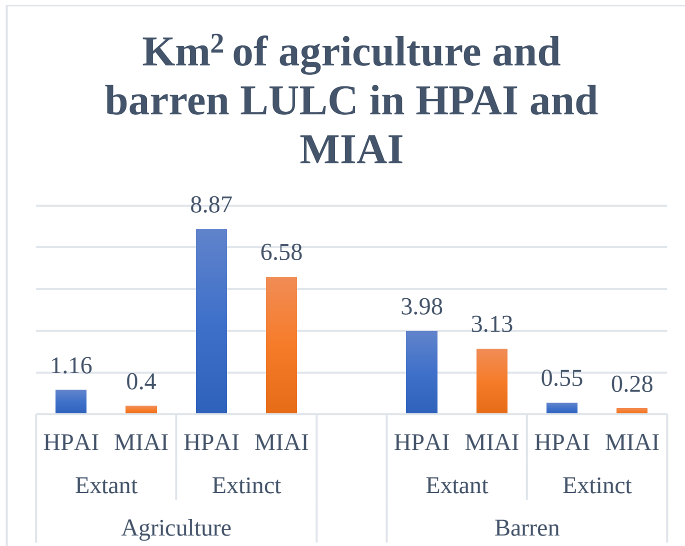

Figure 4, the sum of square kilometres of the LULC classes "agriculture" and "barren", comparing HPAI to MIAI.

4.1.2 Comparing LULC of the 1950s to the 2010s of extant habitats and extinct habitats.

Habitat composition of extant and extinct habitats show no significant differences when comparing HPAI to MIAI, meaning that adverse habitat characteristics (overabundance of agriculture and lack of barren land types) were already present in extinct habitats before the 1950s and did not develop in the following decades. In addition, habitat openness did not change for either extant or extinct habitats between the 1950s and 2010s, Table 4.

Table 4, t-tests of LULC change of extant habitats between 956-2016.

LULC Class	Extant p	Extinct p
Agriculture	0.810	0.535
Barren	0.383	0.284
Forest	0.096	0.456
Herbaceous	0.710	0.174
Urban	0.073	0.318
Wetland	0.444	1.000
Water	0.696	1.000
Open	0.444	0.918
Covered	0.053	0.456

4.2 ACCURACY ASSESSMENT

The classification accuracies of the five randomly selected habitats were evaluated and presented in confusion matrices as shown in Appendix C – Confusion matrices, where supplementary details can be found. Based on the confusion matrixes, Table 5 is created, which reports the Overall Accuracy (OA) and Kappa Coefficient (KC) of the Historical Panchromatic Aeroplane Imagery (HPAI) and Modern Infrared Aeroplane Imagery (MIAI) classifications. The accuracy assessments show how well the classification maps of the five assessed *B. viridis* habitats reflect reality. Generally, OA and KC need to be 85% or higher to be considered accurate representations of reality.

The results show that HPAI and MIAI classifications represent features in the field at a sufficient level. However, the probability of this being due to chance is slightly higher than preferred. HPAI classifications generally reflected reality better than MIAI classifications, Table 5.

All five assessed HPAI and MIAI classifications achieved OA of over 85%, meaning there is sufficient probability that a certain feature of an area in the field is correctly classified. Two out of five assessed HPAI classifications achieved KC of over the standard of 85% (Kungstorp, 88.2% & Ven, 88.4%) and one out of five for MIAI classifications (Kungstorp, 88.2%). The lowest HPAI classification KC is 77.2%, and 81.2% for MIAI classifications, while the mean KC of HPAI classifications is 84.2% and 84% for MIAI classification. This indicates that the chance that the classification is correct due to chance only is close to acceptable levels, where 100% KC shows that there was perfect agreement between the created classification maps and reality, and -100% shows no agreement with reality at all.

Table 5, OA and KC of the five randomly selected B. viridis habitats for HPAI and MIAI classifications.

Habitat name		HPAI	MIAI
Vellinge västra trädgård	KC	77.2%	83.7%
	OA	88.7%	88.8%
Kungstorp	KC	88.2%	88.2%
	OA	90.1%	89.9%
Klagshamn	KC	84.5%	84.3%
	OA	88.4%	87.1%
Ottenby södra udde	KC	82.9%	82.7%
	OA	85.7%	86.2%
Ven	KC	88.4%	81.2%
	OA	92.1%	86.8%
Kappa Coefficient	Max	88.4%	88.2%
	Min	77.2%	81.2%
	Mean	84.2%	84.0%
Overall Accuracy	Max	92.1%	89.9%
	Min	85.7%	86.2%
	Mean	89.0%	87.8%

5 DISCUSSION

This study was designed to identify differences between extant and extinct habitats of *B. viridis*. The results of this study show significant differences in habitat composition between extant and extinct *B. viridis* habitats in the 1950s and the 2010s, the main differences being the significant amount of agriculture and the lack of barren land in extinct habitats. However, no significant difference in habitat openness was found between extant and extinct habitats. Furthermore, the lack of barren land and a significant amount of agriculture were already present in extinct habitats before the 1950s.

5.1 LAND USE AND LAND COVER

In recent decades agriculture has reached prominence in politics for its adverse effects on the environment and biodiversity. This study indicates that agriculture affects *B. viridis* habitats and possibly contributed to the decline of this toad species in Sweden. Engström's environmental assessment (2007) of Sweden's agriculture illustrates that agriculture has contributed to eutrophication and overabundant resource use, such as pesticides and fertilizer [31]. These findings are supported by Piha (2006), who found that agricultural expansion and intensification, particularly overabundant pesticide use in wetlands, negatively affect amphibians in their larval and adult stages. However, there are added adverse effects on amphibians as the impacts of intensive agriculture are more apparent when amphibians face multiple environmental stressors [28], such as the lack of barren land. Sawatsky and Fahrig (2018) also point out that in areas that experience wetland loss due to agricultural activities and expansion, it is better to implement landscape-scale terrestrial habitat protection guidelines instead of focusing on wetland protection [52]. This study shows that the adverse amount of agriculture was already present before the 1950s. Fredh and Mazier (2016) reinforce this finding and indicate that Swedish agriculture intensified in the 1930s when grasslands made way for croplands [12].

This study showed that the amount of barren land and agriculture in *B. viridis* habitats did not change between the 1950s and the 2010s, suggesting that the critical threshold for barren land and impacts of agriculture were exceeded a long time ago. This suggests that the decline of the *B. viridis* population was a delayed and slow process. Jackson and Sax (2009) and Kuussasri et al. (2009) support this suggestion and show that local extinction can occur with a substantial delay [53]. However, populations of species that are predicted to go extinct can still be restored through habitat restoration and landscape management [54], further supporting the need for the protection of terrestrial habitats as expressed by Sawatsky and Fahrig, 2018 [52].

B. viridis is known to be adapted to dry and open habitats [15]. The lack of barren land types in extinct habitats, which is reflected in this study's results, is a contributing factor to the population decline of *B. viridis*. The crucial role of barren habitats is corroborated by Cabela (1990), who showed that by the 1980s, *B. viridis* disappeared in most of its habitats in Vienna due to the destruction of summer habitats (barren land types) and breeding habitats. Coincidently, Cabela's study also indicated that the use of pesticides in agriculture contributed to the decreased toad populations, which explains the *B. viridis* population decline in Sweden [27]. Vences et al. (2003) found that the disappearance of gravel pits caused the population of *B. viridis* to drastically decline [55], further suggesting the importance of barren land types for *B. viridis*.

As this study suggests, agriculture expansion and intensification, and the loss of barren land types (higher area of barren land in extant habitats) could have adversely affected *B. viridis* habitats and decreased its populations. Andrén (1999) supports this finding [26], who found that habitat loss is complemented by smaller habitat sizes and isolation, causing reduced populations and increased migration. The scattered populations are additionally stressed due to road mortality [32].

All in all, this study's results and literature strongly indicate that *B. viridis* habitats are affected by intense agricultural activities. This, combined with the lack of barren land in extinct habitats, could have contributed to habitat fragmentation and thus reduced the population of *B. viridis* in Sweden. As Piha (2006) [28] suggested, an additional stressor combined with intensive agriculture could have caused *B. viridis* populations to decline. However, the similarities in habitat openness of extant and extinct habitats in this study suggest that degree of habitat openness is unlikely to have contributed to the decline of *B. viridis* populations.

5.2 METHOD

The results of a classification map are heavily influenced by the type and quality of the used imagery [48]. While classifying, it was found that Historical Panchromatic Aeroplane Imagery (HPAI) and Modern Infrared Aeroplane Imagery (MIAI) often had LULC with similar spectral properties, which increased the number of misclassifications. For example, while classifying HPAI, water was often a black colour similar to rooftops, suggesting that it might be good practice to lower the minimum acceptable accuracy levels as suggested by Foody (2008) [49]. Furthermore, while the spectral detail level of the used images was 0.5m, at times, it was found to be challenging to distinguish urban objects and LULC for this study's desired classification detail level. This suggests that it might be better to classify urban and similar areas as a whole and not by their components, such as roads, gardens and houses.

HPAI was contrast-corrected as suggested by Bolles and Forman (2018) [44], which considerably improved image quality. This study achieved a similar or higher average Overall Accuracy (OA, 89%) and Kappa Coefficient (KC, 84,4%) than other studies that classified HPAI. A similar accuracy assessment method was used by Clifford et al., 2011, who attained up to 96% OA using a Supervised Machine Learning (SML) classifier [51]. Carmel and Kadmon (1998) reported OA values of up to 58% for 1960s HPAI when using an SML classifier [33]. However, since their study in 1998, technology has significantly improved, possibly making classifications performed in the 2020s more accurate. Neither study reported KC, making comparisons with their studies incomplete. Nevertheless, similar results are reported by Okeke and Karnieli (2006), who exceeded 85% OA and 80% KC, respectively [42]. The comparisons indicate that the ICUC combined with post-processing and manual correction performs similarly to SML methods when classifying HPAI.

Interestingly, the classifications of MIAI achieved lower average OA (87.8%) and KC (84%) values than the HPAI classifications (OA = 89% & KC = 84.2%. The ICUC of Hasmadi et al. (2009) achieved lower OA (80,56%) and KC (73,65%) [47]. These lower values could be attributed to the lack of post-processing in their study. Srivastava et al. (2012) compared the performance of three SML classifiers: MLC (OA = 82,3%, KC = 71,1%), SVM (OA = 84,9%, KC = 75%) and ANN (OA = 84,9%, KC = 75%) [41], which were less accurate than the method in this study. However, a possible explanation for their lower OA and KC could be the lower pixel detail of 30m of their used imagery. This indication is strengthened due to Hasmadi et al., 2009, using SPOT 5 satellite imagery with a pixel detail of 10m, suggesting that higher OA and KC values can be achieved when using higher pixel detail imagery.

It should be noted that the manual correction used in this study is vulnerable to misinterpretations by the user and thus misclassifications of an area's LULC. In addition, the accuracy assessment used in this study, which is similar to the assessment method used by Clifford et al. (2011) [51], assessed the classification maps by comparing them to the same imagery upon which they are based. However, this accuracy assessment method is vulnerable to errors due to human misinterpretations, like manual corrections. Therefore, one must get familiar with the target area by, for example, visiting, studying high-resolution photos and maps, or both. However, the user should be cautious when visiting an area on a different date than when the classification is done because changes to LULC might have occurred.

Remote sensing is a valuable tool when identifying area changes over time, as suggested by Cawkwell et al. (2016) [13]. However, as Morales et al. (2019) indicate [45], many steps and decisions can influence the accuracy of the created classification map throughout the classification process. Unsupervised remote sensing using the ISO-cluster unsupervised classifier combined with post-processing and manual correction shows comparable results to similar studies. However, human interpretation of photos and using the same imagery to assess the classification accuracy make the method prone to inaccuracies and thus potentially unreliable classification maps. Nevertheless, remote sensing can produce reliable classification maps with knowledge of the various classification methods, their vulnerabilities, appropriate materials and imagery. This, combined with familiarity of the target habitat, either through visits or examining high-resolution photos or maps, show potential for a relatively easily applicable classification method when classifying panchromatic and infrared imagery.

6 CONCLUSION

The project aimed to determine if differences in habitat composition between extant and extinct *B. viridis* habitats could have contributed to the decline of the species in Sweden. The comparison was made by remote sensing seven extant and seven, in 2022, extinct *B. viridis* habitats. Classifications were performed on panchromatic historical aeroplane photographs (1956-1967) and modern infrared aeroplane imagery (2008-2016).

This study shows significant habitat composition differences between extant and extinct *B. viridis* habitats in the 1950s and the 2010s. Adverse area characteristics (overabundant agriculture and lack of barren land) were present in extinct habitats before the 1950s, as no significant habitat change has occurred since then. This indicated that the critical thresholds for barren land and agricultural impacts were exceeded long ago and that the decrease of the *B. viridis* population in Sweden was a delayed and slow event. Habitat openness is unlikely to have contributed to the decline of *B. viridis* populations because no significant difference was found between extant and extinct habitats. However, extinct habitats contained much more agriculture and much less barren lands in the 1950s and 2010s. The combination of these adverse habitat characteristics could have contributed to decreasing *B. viridis* populations through reducing habitat sizes, habitat fragmentation, and increased and further migration.

The remote sensing method of this study shows promising results and shows the necessity of unsupervised classification in combination with high-resolution imagery, post-processing and manual correction. However, the probability that features in the field are classified correctly due to chance is slightly higher than preferred. Human interpretation of areas and manual correction show vulnerabilities to errors and thus potentially inaccurate classification maps. The method's reliability depends on the user's familiarity with the target habitats, making it essential that the user familiarises oneself through visits or examination of photos and maps before classifying areas. Nevertheless, the method produces maps that represent features in the field satisfactorily.

In conclusion, Nordens Ark could incorporate remote sensing in their conservation strategy to identify suitable reintroduction sites and habitats for the European Green Toad.

7 RECOMMENDATIONS

Several practical actions can be taken to help reintroduce and conserve *B. viridis* in Sweden. Further conservation efforts should focus on habitats with much barren land and relatively little agriculture. Furthermore, habitats in an area with intensive agriculture can be fortified by implementing guidelines for conservation efforts by protecting terrestrial habitats on a landscape level. The terrestrial habitat protection guidelines can be incorporated in the *B. viridis* species action plan of the Swedish environmental agency Naturvårdsverket and implemented by the various Swedish county boards. In addition, additional habitats can be created to reduce the effects of habitat isolation, habitat fragmentation and mortality due to migration. When creating new habitats, the focus should be on choosing an area with minimal agriculture and on creating barren land.

When using remote sensing for conservation purposes, it is recommended to use imagery with a high pixel detail. Before the target habitats are remotely sensed, it is highly advisable to familiarize oneself with the areas through visits or examination of high-resolution photos and maps. Familiarisation will result in better interpretation of the habitat composition and improved accuracy when classifying. In the classification process, it is recommended to classify urban areas as a whole and not by their components, such as roads, gardens and houses. The generalisation of such areas will reduce inaccuracies and increase the reliability of the final classification map.

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APPENDIX A – EUROPEAN GREEN TOAD HABITATS

Table 6, B. viridis habitats used in this study [9].

Habitat location	Latitude	Longitude	Last year of toad activity	State
Vellinge västra trädgård	55.458043	12.99209	2008	Extinct
Gessie ängar	55.497423	12.94245	2009	Extinct
Vellinge norra	55.476107	12.95842	2009	Extinct
Ven	55.911694	12.68445	2009	Extinct
Hammars näs	55.449659	12.94732	2010	Extinct
Jordbroskogen	55.751602	12.97793	2010	Extinct
Kungstorp änger	55.441515	12.97262	2010	Extinct
Linhamns kalkbrott	55.567592	12.93283	2021	Extant
Klagshamn	55.521948	12.91457	2021	Extant
Lernacken	55.565045	12.89151	2021	Extant
Ottenby södra udde	56.195932	16.39916	2021	Extant
Landakrahamnen	55.859484	12.84879	2021	Extant
Högby hamn	57.168936	17.0343	2021	Extant
Utklippan	55.952687	15.70286	2021	Extant

APPENDIX B – THE SUM OF SQUARE KILOMETRES PER LULC

Table 7, the sum of square kilometers of all habitats per LULC class subdivided by state and time.

LULC	State	Time	Km²
Agriculture	Extant	HPAI	1.16
	Extant	MIAI	0.4
	Extinct	HPAI	8.87
	Extinct	MIAI	6.58
Barren	Extant	HPAI	3.98
	Extant	MIAI	3.13
	Extinct	HPAI	0.55
	Extinct	MIAI	0.28
Forest	Extant	HPAI	0.49
	Extant	MIAI	2.12
	Extinct	HPAI	1.67
	Extinct	MIAI	1.85
Herbaceous	Extant	HPAI	4.88
	Extant	MIAI	5.57
	Extinct	HPAI	5.06
	Extinct	MIAI	7.99
Urban	Extant	HPAI	0.14
	Extant	MIAI	1.33
	Extinct	HPAI	0.2
	Extinct	MIAI	0.6
Water	Extant	HPAI	9.47
	Extant	MIAI	7.92
	Extinct	HPAI	3.53
	Extinct	MIAI	3.38
Wetland	Extant	HPAI	2.11
	Extant	MIAI	1.3
	Extinct	HPAI	1.88
	Extinct	MIAI	1.41
Open	Extant	HPAI	2.16
	Extant	MIAI	1.85
	Extinct	HPAI	1.99
	Extinct	MIAI	1.96
Covered	Extant	HPAI	0.63
	Extant	MIAI	3.46
	Extinct	HPAI	1.87
	Extinct	MIAI	2.45

APPENDIX C – CONFUSION MATRICES

This appendix presents the confusion matrices of the five accuracy assessed habitats. The overall accepted accuracy standard is 85%, or 0.85. Values that are below that accepted standard are highlighted in red.

Vellinge västra trädgård 1962

Class	Grass	Structures	Bushes and trees	Bare mineral soil	Agriculture	Total	U_Accuracy	Kappa
Grass	8	1	1	0	0	10	0,800	0
Structures	0	8	2	0	0	10	0,800	0
Bushes and trees	1	0	8	0	1	10	0,800	0
Bare mineral soil	0	1	0	4	5	10	0,400	0
Agriculture	0	0	2	0	82	84	0,976	0
Total	9	10	13	4	88	124	0	0
P_Accuracy	0,889	0,800	0,615	1,000	0,932	0	0,887	0
Kappa	0	0	0	0	0	0	0	0,772

Vellinge västra trädgård 2010

Class	Grass	Structures	Bushes and trees	Bare mineral soil	Agriculture	Roads	Total	U_Accuracy	Kappa
Grass	17	2	1	1	0	0	21	0,810	0
Structures	0	10	0	0	0	0	10	1,000	0
Bushes and trees	1	1	5	0	1	2	10	0,500	0
Bare mineral soil	0	0	0	10	0	0	10	1,000	0
Agriculture	2	0	0	0	62	0	64	0,969	0
Roads	0	2	0	1	0	7	10	0,700	0
Total	20	15	6	12	63	9	125	0	0
P_Accuracy	0,850	0,667	0,833	0,833	0,984	0,778	0	0,888	0
Kappa	0	0	0	0	0	0	0	0	0,837

Kungstorp 1962

Class	Reeds	Wetland	Grass	Water	Agriculture	Structures	Bushes and trees	Bare mineral soil	Total	U_Accuracy	Kappa
Reeds	9	0	1	0	0	0	0	0	10	0,900	0
Wetland	0	10	0	0	0	0	0	0	10	1,000	0
Grass	3	4	23	1	0	0	0	0	31	0,742	0
Water	0	2	1	31	0	0	0	0	34	0,912	0
Agriculture	0	0	1	0	15	0	0	0	16	0,938	0
Structures	0	0	0	0	0	10	0	0	10	1,000	0
Bushes and trees	0	0	0	0	0	0	10	0	10	1,000	0
Bare mineral soil	0	0	0	0	0	0	0	10	10	1,000	0
Total	12	16	26	32	15	10	10	10	131	0	0
P_Accuracy	0,750	0,625	0,885	0,969	1,000	1,000	1,000	1,000	0	0,901	0
Kappa	0	0	0	0	0	0	0	0	0	0	0,882

Kungstorp 2010

Class	Water	Agriculture	Wetland	Grass	Short grass	Structures	Roads	Bushes and trees	Total	U_Accuracy	Kappa
Water	27	0	1	0	0	0	0	0	28	0,964	0
Agriculture	0	16	0	1	0	0	0	0	17	0,941	0
Wetland	0	0	17	4	0	0	0	0	21	0,810	0
Grass	0	0	1	21	0	0	0	0	22	0,955	0
Short grass	0	0	1	1	9	0	0	0	11	0,818	0
Structures	1	0	0	0	0	9	0	0	10	0,900	0
Roads	0	0	0	0	0	0	10	0	10	1,000	0
Bushes and trees	0	3	0	0	0	0	0	7	10	0,700	0
Total	28	19	20	27	9	9	10	7	129	0,000	0
P_Accuracy	0,964	0,842	0,850	0,778	1,000	1,000	1,000	1,000	0	0,899	0
Kappa	0	0	0	0	0	0	0	0	0	0	0,882

Klagshamn 1962

Class	Water	Wetland	Bare mineral soil	Grass	Structures	Bushes and trees	Total	U_Accuracy	Kappa
Water	21	2	0	0	0	0	23	0,913	0
Wetland	0	6	0	4	0	0	10	0,600	0
Bare mineral soil	0	0	12	0	0	1	13	0,923	0
Grass	0	1	0	42	0	3	46	0,913	0
Structures	0	0	1	0	9	0	10	0,900	0
Bushes and trees	0	0	0	1	0	9	10	0,900	0
Total	21	9	13	47	9	13	112	0	0
P_Accuracy	1,000	0,667	0,923	0,894	1,000	0,692	0	0,884	0
Kappa	0	0	0	0	0	0	0	0	0,845

Klagshamn 2010

Class	Water	Wetland	Bare mineral soil	Grass	Structures	Bushes and trees	Sealed concrete surface	Roads	Total	U_Accuracy	Kappa
Water	16	0	0	0	0	0	0	0	16	1,000	0
Wetland	0	8	0	2	0	0	0	0	10	0,800	0
Bare mineral soil	0	0	10	0	0	0	0	0	10	1,000	0
Grass	0	6	0	26	0	4	0	0	36	0,722	0
Structures	1	0	0	0	8	1	0	0	10	0,800	0
Bushes and trees	0	0	0	2	0	34	0	1	37	0,919	0
Sealed concrete surface	0	0	0	0	0	0	10	0	10	1,000	0
Roads	0	0	0	0	0	1	0	9	10	0,900	0
Total	17	14	10	30	8	40	10	10	139	0	0
P_Accuracy	0,941	0,571	1,000	0,867	1,000	0,850	1,000	0,900	0	0,871	0
Kappa	0	0	0	0	0	0	0	0	0	0	0,843

Ottenby 1956

Class	Water	Wetland	Wall	Grass	Structures	Bushes and Trees	Bare mineral soil	Road	Total	U_Accuracy	Kappa
Water	35	1	0	0	0	0	2	0	38	0,921	0
Wetland	1	24	0	6	0	0	1	0	32	0,750	0
Wall	0	0	7	0	0	0	3	0	10	0,700	0
Grass	0	1	0	19	0	0	0	0	20	0,950	0
Structures	0	0	0	4	6	0	0	0	10	0,600	0
Bushes and Trees	0	0	0	0	0	10	0	0	10	1,000	0
Bare mineral soil	0	0	0	0	0	0	10	0	10	1,000	0
Road	0	0	0	0	0	0	1	9	10	0,900	0
Total	36	26	7	29	6	10	17	9	140	0	0
P_Accuracy	0,972	0,923	1,000	0,655	1,000	1,000	0,588	1,000	0	0,857	0
Kappa	0	0	0	0	0	0	0	0	0	0	0,829

Ottenby 2008

Class	Water	Wetland	Grass	Structures	Bushes and trees	Bare mineral soil	Roads	Total	U_Accuracy	Kappa
Water	40	0	0	0	0	0	0	40	1,000	0
Wetland	0	20	3	0	0	0	0	23	0,870	0
Grass	0	8	19	0	0	0	0	27	0,704	0
Structures	0	0	0	9	0	1	0	10	0,900	0
Bushes and trees	0	0	0	0	10	0	0	10	1,000	0
Bare mineral soil	5	1	0	0	0	4	0	10	0,400	0
Roads	0	0	0	0	0	0	10	10	1,000	0
Total	45	29	22	9	10	5	10	130	0	0
P_Accuracy	0,889	0,690	0,864	1,000	1,000	0,800	1,000	0	0,862	0
Kappa	0	0	0	0	0	0	0	0	0	0,827

Ven 1965

Class	“agriculture”	Bushes and trees	Grass	Structures	Bare Mineral soil	Water	Sealed concrete & stone surfaces	Total	U_Accuracy	Kappa
“agriculture”	71	1	2	0	0	0	0	74	0,959	0
Bushes and trees	1	9	0	0	0	0	0	10	0,900	0
Grass	0	3	11	0	0	0	1	15	0,733	0
Structures	0	0	0	10	0	0	0	10	1,000	0
Bare Mineral soil	1	0	0	2	7	0	0	10	0,700	0
Water	0	0	0	0	0	10	0	10	1,000	0
Sealed concrete & stone surfaces	0	0	0	0	0	0	10	10	1,000	0
Total	73	13	13	12	7	10	11	139	0	0
P_Accuracy	0,973	0,692	0,846	0,833	1,000	1,000	0,909	0	0,921	0
Kappa	0	0	0	0	0	0	0	0	0	0,884

Ven 2016

Class	“agriculture”	Bushes and trees	Grass	Structures	Bare mineral soil	Water	Roads	Total	U_Accuracy	Kappa
“agriculture”	65	0	1	0	1	0	0	67	0,970	0
Bushes and trees	0	8	1	1	0	0	0	10	0,800	0
Grass	2	2	14	1	0	0	0	19	0,737	0
Structures	1	0	0	8	1	0	0	10	0,800	0
Bare mineral soil	0	1	4	0	4	0	1	10	0,400	0
Water	0	0	0	0	0	10	0	10	1,000	0
Roads	1	0	0	0	0	0	9	10	0,900	0
Total	69	11	20	10	6	10	10	136	0	0
P_Accuracy	0,942	0,727	0,700	0,800	0,667	1,000	0,900	0	0,868	0
Kappa	0	0	0	0	0	0	0	0	0	0,812