

Historical habitat mapping from black-and-white aerial photography: A proof of concept for post World War II Switzerland

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ARTICLE INFO

Keywords:

Active learning
Forest
Grassland
Object-oriented
Classification
Segmentation
Wetland

ABSTRACT

Information regarding the spatial arrangement and extent of past habitats is important for understanding present biodiversity, restoration potential, and fighting extinction-debt effects. European landscapes have changed profoundly over recent decades, with the trend accelerating following World War 2. We develop a proof of concept for mapping historic habitat distribution for Switzerland from black and white aerial imagery compatible with the present-day habitat map. Recently available orthorectified 1946 aerial imagery (1 m resolution) was segmented based on spectral and shape characteristics for training areas (320–508 km²) representing the main biogeographical regions of Switzerland. Initial training data was derived by manual aerial orthoimage interpretation differentiating 15 habitat classes. A random forest model was trained to classify the segments using variables describing spectral information, image texture, segment shape, topography, climate, and anthropogenic influence. Classification accuracy was improved with additional training samples derived in a stepwise approach, applying three different sampling techniques. Highest class accuracies (producer's and user's accuracies ≥ 0.75) were achieved for the habitats 'Standing water', 'Flowing water', 'Glaciers, permanent ice and snow', and 'Forests and other wooded land'. Particularly low user's accuracies were found for 'Wetlands', 'Hedges and tree rows' and 'Buildings'. The comparison to independent data further revealed minor differences in overall accuracy for the three different sampling strategies. Yet, map predictions sometimes varied substantially, indicating that the sampling strategies address different classification issues. Hence, we conclude that combining different sampling strategies for training data collection has the potential to improve the mapping, particularly in the case of multi-class classifications.

1. Introduction

Habitat maps distinguishing plant communities are an increasingly important tool for the planning, management and monitoring of biodiversity, ecosystems, and nature's contribution to people (European Environmental Agency, 2014). Newest remote sensing data and techniques, as well as open data policies, offer novel opportunities to differentiate habitats at high spatial and thematic resolution over broad extents. Hence, nation-wide habitat maps are becoming increasingly available (e.g., Butler and Sanderson, 2022). For Switzerland, the current distribution of habitats has recently been mapped at very high spatial and thematic resolution based on remote sensing data (Price

et al., 2023).

In many countries, changes in agricultural intensity, settlement growth and the associated expansion of infrastructure have profoundly reshaped landscapes in recent decades (Plieninger, 2017), and hence the habitats and species present therein. Such changes result in habitat loss and decreased connectivity, which has negative consequences for biodiversity (e.g., Olsen et al., 2018). Species may disappear due to habitats changes or persist for some time despite unfavourable conditions, resulting in an extinction debt (Jamin et al., 2020; Haddou et al., 2022). In such cases, conservation measures may prevent future extinctions. One major challenge to identify extinction debts is to find appropriate information about the distribution and extent of habitats in

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<https://doi.org/10.1016/j.jag.2025.104464>

Received 23 December 2024; Received in revised form 10 February 2025; Accepted 4 March 2025

Available online 8 March 2025

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the past (Jamin et al., 2020). Furthermore, due to a lack of information on past conditions, shifting baselines can lead to a gradual change in the accepted norms of the condition of the environment. Hence, there is a growing need for baseline data to track, understand and monitor changes in landscapes/biodiversity through time. The choice of a baseline is decisive because different base years may lead to very different conclusions. Yet, this choice is often defined by data availability and hence arbitrary with respect to the ecology of the ecosystem or species examined (Magurran et al., 2010, Soga and Gaston, 2018).

In Europe in particular, accelerated landscape change began after the Second World War due to the increasing availability of fossil energy (Antrop, 2000). Typical changes include the increase in settlement area and infrastructure in the lowlands or forest regrowth in more remote areas (Lachat et al., 2010). Land consolidation projects, agricultural intensification and land abandonment led to a strong decline in traditional agricultural landscape structure, characterised by small parcel sizes, low nutrient availability, and the abundance of small structures (e.g., hedges, creeks) and fruit trees (Hersperger and Bürgi, 2010). An overview of the extent and spatial distribution of habitats in the late 1940s, i.e., before landscapes began to change at an increasing rate, would therefore be highly valuable for understanding present biodiversity patterns and fighting extinction debt effects.

To accurately map historic habitat distributions, appropriate high-quality data is key yet often one of the most limiting factors (Kuussaari et al., 2009). While historical maps provide valuable information about landscapes in the past (Gimmi et al., 2011), they are often incomplete with respect to habitat types considered or restricted to specific areas of interest. Satellite imagery dates at its earliest back to the first Landsat mission in 1972 (Nasa, 2023). As the oldest form of remote sensing data, aerial black and white (B&W) photographs, collected since the early 1930s (Paine and Kiser, 2012) provide detailed, spatially complete historic landscape information for large spatial extents (Morgan and Gergel, 2010). For Switzerland, an historical country-wide orthoimage dataset collected in 1946 has recently become publicly available (Swisstopo, 2019).

Several studies have developed methods for automated or semi-automated mapping based on the limited panchromatic spectral information of B&W aerial imagery (e.g., Vogels et al., 2017, Wang et al., 2022, Kindermann et al., 2023). While some studies are pixel-based (e.g., Wang et al., 2022), others apply geographic object-based image analysis (GEOBIA) e.g., Lydersen and Collins, (2018). In this approach, the image is first divided into image segments representing coherent landscape elements. These segments are then labelled with the help of a classifier, such as a random forest (RF) model (Breiman, 2001). One major challenge, particularly in the context of historic mapping, is the collection of training data, which is decisive for the quality of the mapping product (Maxwell et al., 2018). Ideally, the training data consists of a sufficiently large number of high-quality training samples representing the full variability of the classes to be mapped (Tuia et al., 2011). Since historic field data is usually scarce, visual interpretation of the aerial B&W images, potentially informed by ancillary data, can be used for deriving training samples (Lydersen and Collins, 2018). Thereby, a sampling strategy needs to be defined, for example random sampling (Vogels et al., 2017, Lydersen and Collins, 2018). Existing mapping studies based on B&W aerial imagery typically focus on identifying one or few specific habitat or land use/land-cover types, such as cropland (Vogels et al., 2017), forest or trees (Wang et al., 2022, Lydersen and Collins, 2018), or few broad land cover classes (Caridade et al., 2008).

This study aimed at exploring the feasibility of deriving an area-wide historical habitat map for Switzerland. Switzerland is an ideal study region as it is characterised by diverse environmental and cultural conditions, ranging from densely populated lowlands to inaccessible alpine environments, thus hosting a high number of habitats (Delarze et al., 2015).

The objectives of this study were:

- 1) to define habitat classes, compatible with the current habitat map of Switzerland (Price et al., 2023) which allow for an area-wide historical classification, specifically for 1946;
- 2) to develop a method to map the historic distribution of these habitat classes that can be applied without region-specific adjustments;
- 3) to determine the most effective sampling strategy for mapping improvement;
- 4) to assess the overall accuracy of the map derived as well as class-specific accuracies and identify habitat classes that will require special attention in future applications of the developed method.

GEOBIA is used to derive image segments based on the orthorectified composite of aerial photographs from 1946. Initial training data was collected by manual aerial orthoimage interpretation and used to train a RF model. The predictors describe spectral information, image texture, segment shape, topography, climate and anthropogenic information. To increase the accuracy of the initial classification, additional training data was collected following three sampling strategies. Finally, the predictions were compared to regularly distributed independent data.

2. Material and methods

2.1. Training areas

Switzerland can be divided into six biogeographical regions defined by the spatial distribution of flora and fauna (Gonseth et al., 2001; Fig. 1). For this study, training areas were defined in all biogeographical regions (Fig. 1; Table 1). The areas were selected to include characteristic landscapes as well as all habitats typically occurring in the respective biogeographical area, and therefore cover large elevation gradients and various aspects. In the case of the Central Plateau, three training areas were selected to cover the heterogeneity of the region. Ideally, historical habitat maps were available for the training areas, or parts of them, to inform the training data generation.

2.2. Defining habitat classes

Habitat classes were defined based on the Swiss habitat typology (TypoCH; Delarze et al., 2015), which can be translated to the pan-European classification system EUNIS (European Nature Information System taxonomies, Chytrý et al., 2020). TypoCH is widely used to define habitat types in Switzerland, including for the current country-wide habitat map of Switzerland (Price et al., 2023). This hierarchical typology distinguishes nine habitat classes (see first column in Table 2), which are further divided into habitat groups and types.

Following the TypoCH typology, we defined 15 habitat classes identifiable in the B&W imagery (Table 2). These classes cover all nine TypoCH classes except for 'Pioneer vegetation of disturbed areas' and distinguish, where possible, between TypoCH habitat groups. In addition, the auxiliary class *Shadows* was used to allow for area-covering mapping in areas where shadows make determination of habitat class impossible.

2.3. Image classification

An overview of the image classification approach is visualised in Fig. 2. The overall approach was GEOBIA (Blaschke, 2010), where segments (also referred to as image objects) were derived and subsequently labelled using a classification algorithm. In contrast to single pixels, segments are characterised by additional spatial (e.g., shape) and spectral information (e.g., mean or standard deviations per band), which is highly valuable for image classification, especially in the context of the limited panchromatic spectral information of B&W images. Initial training data was collected by manual aerial orthoimage interpretation differentiating the habitat classes defined in Table 2. With this data, a single random forest (RF) model for all training areas (Breiman, 2001)

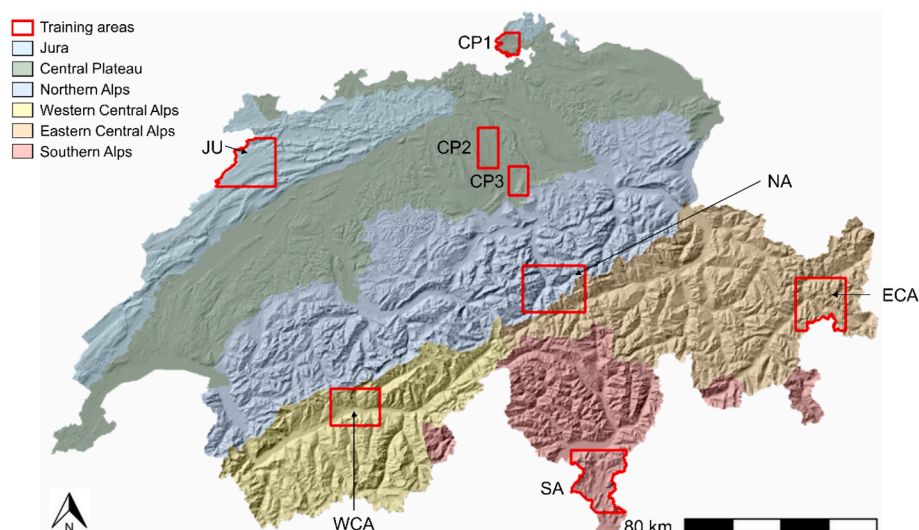


Fig. 1. Training areas within the biogeographical regions (Gonseth et al., 2001; © FOEN), overlaid on the topographical relief (DHM25 © 2005 swisstopo).

Table 1

Characteristics of the training areas. Elevation was extracted from the digital elevation model DHM25 (Swisstopo, 2005). Historic temperature and precipitation data were provided by the Land Change Science Unit at WSL (Birmensdorf, Switzerland), extracted from daily gridded maps (Thornton et al., 1997) derived from MeteoSwiss (Federal Office of Meteorology and Climatology) weather stations. T: Annual temperature 1941–1950 (mean $\pm$ SD); P: Annual precipitation sum 1941–1950 (mean $\pm$ SD).

Biogeographical region	Area	Region	Extent [km ²]	Elevation range [m asl]	T [C°]	P [mm]	Landscape characteristics	Main historical agricultural uses (Brockmann-Jerosch, 1927)
Jura	JU	Franches Montagnes	368	443–1407	6.9 $\pm$ 0.9	1284 $\pm$ 108	High plateau dominated by large pastures intermixed with conifers and bogs; sparsely populated	clover-grass cultivation, arable farming, livestock and horse breeding, extensive permanent pastures at higher elevations
Central Plateau	CP1	Unterklättgau	76	398–806	8.8 $\pm$ 0.4	816 $\pm$ 48	Agricultural area and one of the bread baskets of Switzerland	three-field system and viticulture
	CP2	Reusstal	145	356–864	9.1 $\pm$ 0.6	984 $\pm$ 72	River valley with comparatively many humid habitats and small villages surrounded by orchards	three-field system, grass farming and orchards
	CP3	Zug	100	413–1074	8.7 $\pm$ 0.9	1200 $\pm$ 120	Lakeside town with former alluvial land surrounded by villages, wooded hills and a relatively high proportion of wetlands	grass farming and orchards
Northern Alps	NA	Oberes Reusstal and Cadi	508	454–3319	1.5 $\pm$ 3.3	1716 $\pm$ 288	Valleys in central Switzerland at the northern foot of the Gotthard massif, from valley bottom to wooded slopes, alpine meadows and glaciers	grass farming, alpine farming
Western Central Alps	WCA	Sierre and Leuk	325	506–3168	4.2 $\pm$ 4.1	984 $\pm$ 288	Inner alpine dry valley with river floodplain, hedges, field terraces and vineyards, pine forests, rocky steppe as well as mountain landscape with plateau glaciers	arable farming, viticulture and alpine farming
Eastern Central Alps	ECA	Swiss National Park	407	1246–3177	0.2 $\pm$ 2.2	972 $\pm$ 120	Largest wilderness area in Switzerland dominated by coniferous forest, alpine meadows and a high proportion of vegetation-free areas with scree, rock and snow	within Swiss National Park: none outside Swiss National Park: alpine farming with arable farming
Southern Alps	SA	Lugano	426	193–2225	9.3 $\pm$ 2.6	1644 $\pm$ 144	Rural area in Ticino with large lakeside city surrounded by hilly landscapes with small villages, characteristic chestnut groves and vineyards; insubric climate	in the valleys: hoe-farming, viticulture, chestnuts, double culture terraces in mountainous areas: extensive pasture

was trained. RF is an ensemble classifier, which has been found to be generally more robust to smaller training data sets, mislabelled samples and overfitting than other classifiers (Rodríguez-Galiano et al., 2012). The R package *randomForest* (Breiman et al., 2018) was used with the default parameters and 500 trees. The predictors used (see section 2.3.3) describe spectral information, image texture, segment shape, topography, climate and anthropogenic influence. To further improve the classification and mitigate potential bias introduced by the initial

training data, additional training data was derived from the training areas. Three sampling techniques were applied, where 600 additional samples were collected for each technique. After retraining the RF model, new prediction maps were produced for each sampling technique and for all samples collected. In a last step, the performances of these maps were assessed using regularly distributed independent data (described in section 2.4). Unless otherwise stated, the calculations and analyses were performed in the statistical software R 4.2.2 (R Core

Table 2

Habitat classes. TypoCH refers to the habitat label in the Swiss habitat typology (TypoCH; Delarue et al., 2015).

TypoCH habitat class	Habitat class	Label	TypoCH habitat group/type	EUNIS code (revised classification 2021_1)
Non-marine water bodies (1)	Standing fresh water	<i>Standing Water</i>	1.1	C1
	Running water	<i>Running Water</i>	1.2	C2
Banks, shores and wetlands (2)	Wetlands (incl. fens, transition mires, wet meadows and raised bogs)	<i>Wetland</i>	2.2–2.4	Q
Glaciers, rocks, screes and gravel (3)	Glaciers, permanent ice and snow	<i>Ice/Snow</i>	3.1	U41, U42; U43
	Rocks, screes and gravel	<i>Rock/Scree</i>	3.2–3.4	U2, U3, U7
Grasslands (4)	Grasslands	<i>Grassland</i>	4.0–4.6	E
Woodland edges, tall herb communities, shrubs (5)	Hedges and tree rows	<i>Hedge</i>	5.3	V4, V63
Forests (6)	Forests and other wooded land	<i>Forest</i>	6.0–6.6	T
	Open forests (canopy cover 20 %–60 %)	<i>Open Forest</i>	6.0–6.6	T, R71
	Individual trees and group of trees (1–3 trees)	<i>Tree</i>	6.0	T
Pioneer vegetation of disturbed areas (7)	–	–	–	–
Plantations and cropland (8)	Meadow orchards	<i>Orchard</i>	8.1.4	V61
	Vineyards	<i>Vineyard</i>	8.1.6	V54
	Cropland	<i>Cropland</i>	8.2	V1
Built habitats (9)	Buildings	<i>Building</i>	9.2	J1, J2
	Transport routes	<i>Street</i>	9.3	J4
–	Shadows	<i>Shadow</i>	–	–

Team, 2023).

2.3.1. Image segmentation

Base data for the image segmentation was the SWISSIMAGE HIST 1946 (Swisstopo, 2019) aerial imagery, which is available for the whole of Switzerland. This orthophoto mosaic is an orthorectified composite of black and white aerial photographs taken in summer 1946 by the US-Army Air Forces and provided by Swisstopo. The imagery was segmented for each training area in the software eCognition Developer v10.1, Trimble Germany GmbH: Munich, Germany, with the multi-resolution segmentation algorithm. This algorithm consecutively merges pixels into segments, thereby maximising their respective homogeneity with respect to colour vs shape and smoothness vs compactness. To define optimal values for these parameters, 13 parameter sets were tested for an example map section, where scale, shape and compactness were varied between 80–100, 0.1–0.4 and 0.4–0.6, respectively. After visual inspection of the segmentation results, the best parameter set (scale = 100, shape = 0.3 and compactness = 0.6) was selected and applied to all training areas. After segmentation, the pixel-based object resizing algorithm was applied to remove small individual trees and generalise the segments.

2.3.2. Initial sampling

Initial training data were collected through visual interpretation of the segments. Thereby, three aims were pursued, wherever possible: (1) mitigate class imbalance (Haibo and Garcia, 2009) by collecting 250–300 samples for each habitat class; (2) represent the spectral variability of the entire area of interest (Tuia et al., 2011), with equal shares of sample from all biogeographical areas; and (3) spread samples across the whole extent of the training areas. Furthermore, it was ensured that the samples of a habitat class were located at least 300 m apart from each other to account for spatial autocorrelation (Ploton et al., 2020). For each training sample, the habitat class according to Table 2 was collected. During visual interpretation a reliability attribute was assigned by the image interpreter to address reference data uncertainty (Stehman and Foody, 2019) and could take the values 1 = unsure, 2 = relatively sure or 3 = sure. A mean reliability value was calculated for each habitat class across all samples, showing that the interpreters were least certain about crops and grass and most certain about Standing water and Ice/Snow (Table 3).

To inform and support training data sampling, both Swiss-wide and training-area specific auxiliary information was used including historic regional and national land use, habitat and cartographic mapping. Generally, the Swiss-wide data was used to separate Rock/Scree from

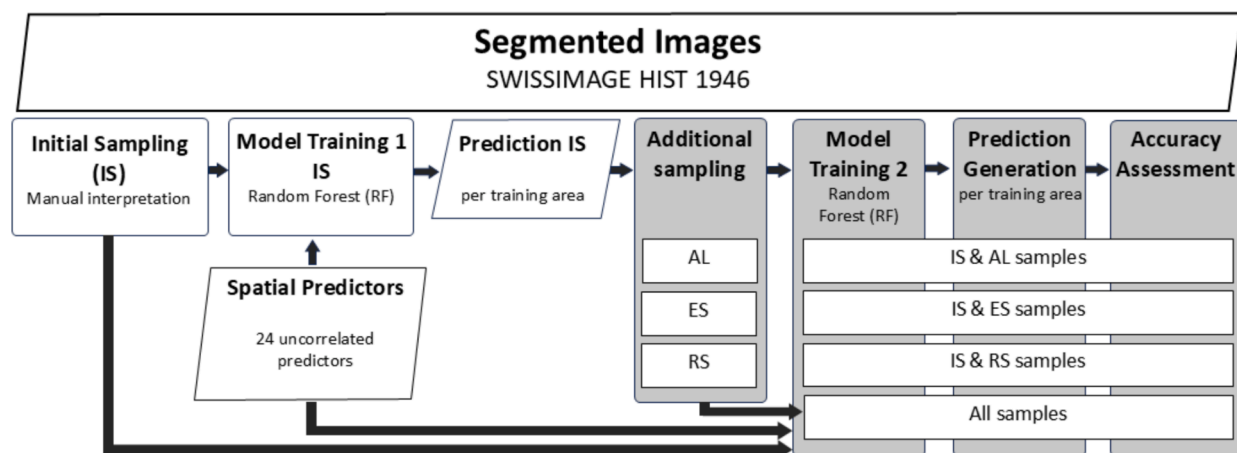


Fig. 2. Overview flowchart depicting imagery classification methodology. The segmented images, which resulted from multi resolution segmentation, are the input data. Following Initial sampling (IS) and the initial prediction, additional sampling is undertaken according to three separate sampling techniques Active learning (AL), Error Sampling (ES) and Random Sampling (RS). Four further predictions are generated, one for each of the three additional sample sets and a fourth using all sample sets.

Table 3

Per-class accuracies for the double classification of 10% of the initial samples. F1 score represents the harmonic mean of user's and producer's accuracy. Mean reliability is the mean value of the reliability attribute recorded during image interpretation.

Class	F1	Mean reliability
<i>Standing Water</i>	1.00	2.99
<i>Running Water</i>	0.92	2.96
<i>Wetland</i>	0.95	2.64
<i>Ice/Snow</i>	0.98	2.98
<i>Rock/Scree</i>	0.76	2.82
<i>Grassland</i>	0.81	2.50
<i>Hedge</i>	0.91	2.86
<i>Forest</i>	0.91	2.87
<i>Open Forest</i>	0.87	2.72
<i>Tree</i>	0.93	2.93
<i>Orchard</i>	0.98	2.68
<i>Vineyard</i>	1.00	2.81
<i>Cropland</i>	0.89	2.30
<i>Building</i>	0.94	2.96
<i>Street</i>	0.98	2.96
<i>Shadow</i>	0.97	2.94

Grassland, while area-specific data was primarily useful to distinguish *Wetland* from *Grassland* and *Cropland*. In total 3,888 samples were collected as initial training data.

To assess the quality of the assignment, 10 % of all samples were randomly selected and also separately classified by a second interpreter (Stehman and Foody, 2019). Overall accuracy was 0.918 (95 % confidence interval: 0.886–0.943). Per-class accuracies assessed with the F-score were highest for the classes *Standing Water* and *Vineyard* and lowest for the class *Rock/Scree* followed by *Grassland* (Table 3).

Table 4

Overview of the predictor metrics calculated per segment. SD: standard deviation, IQR: interquartile range. Predictors/metrics denoted with an asterisk were used for the classification.

Group	Predictor	Metric	Spatial resolution	Description, Reference
Spectral information	Brightness*	Mean*, SD*	1 m	Value of the grey-scale data for an object
	Brightness_DiffN*	Mean*	1 m	Difference in the brightness to neighbouring objects
	Brightness_DiffDN*	Mean*	1 m	Difference in the brightness to the darkest neighbouring object
Segment shape	Area*			Area of the segment
	Asymmetry*			Comparison of the segment shape to an approximated ellipse around the segment
	Border index			Ratio between the border length of the segment and the smallest enclosing rectangle; describes the jaggedness of the segment
	Border length			Border length of the segment
	Compactness			Product of the length and the width, divided by the number of pixels within the segment
	Density			Number of the pixels of the segment divided by its approximated radius
	Length/width ratio*			Length-to-width ratio of the main line of a segment
	Radius_LEE			Radius of largest enclosed ellipse
	Rectangular fit*			Comparison of the segment shape to a rectangle of similar size and proportions
				Derived from grey level co-occurrence matrix (GLCM; Haralick et al., 1973)
Image texture	GLCM contrast*	Mean, SD*, IQR	1 m	
	GLCM correlation*	Mean, SD*, IQR	1 m	
	GLCM entropy*	Mean, SD*, IQR	1 m	
Topography	Curvature profile 5 m*	Mean*, SD*	5 m	Profile curvature (parallel to the maximum slope); filter radius 3 cells; ArcGIS Pro ESRI (v2.8)
	Curvature profile 25 m	Mean, SD	25 m	Profile curvature (parallel to the maximum slope); ArcGIS Pro ESRI (v2.8)
	Eastness*	Mean*, SD*	25 m	Sinus of the aspect; filter radius 3 cells, ArcGIS ESRI (v10.3)
	Flow accumulation*	Mean*, SD*	25 m	Accumulated waterflow, single flow algorithm, ArcGIS ESRI (v10.3)
	Northness*	Mean*, SD*	25 m	Cosinus of the aspect; filter radius 3 cells, ArcGIS ESRI (v10.3)
	Slope*	Mean, SD*	25 m	Slope of the terrain; ArcGIS ESRI (v10.3)
	TPI	Mean, SD	25 m	Topographic position index; Jenness (2006)
	TRI	Mean, SD	25 m	Topographic ruggedness index; (Marchi and Dalla Fontana, 2005)
	TWI*	Mean*, SD*	25 m	Topographic wetness index; FD8 multi-flow direction, filter radius 6 cells; (Freeman, 1991)
Climate	Growing degree days*	Mean*	100 m	Mean yearly growing degree days between 1941 and 1950
Anthropogenic influence	Closest church*	Mean*	1 m	Euclidean distance to closest church

2.3.3. Spatial predictors

We compiled 42 predictors from the following groups: spectral information, segment shape, image texture, topography, climate and distance to settlement (Table 4). Image texture information and ancillary spatial predictors have been shown to improve the classification accuracy for black and white imagery (Manandhar et al., 2009). The predictor set was thinned to 24 by excluding highly correlated predictors (i. e., Pearson correlation coefficient $r > |0.7|$). The predictors describing spectral information and segment shape were calculated for each segment in eCognition Developer v10.1, Trimble Germany GmbH: Munich, Germany, with the B&W aerial imagery serving as base data for the spectral information predictors. Image texture was derived based on the grey level co-occurrence matrix (GLCM) measures contrast, correlation and entropy (Haralick et al., 1973). Contrast and entropy were calculated with the R package glcm (Zvoleff, 2022), while, for correlation, glcmTextures (Ilich, 2023) was used. The three measures were calculated for all directions and a window size of 15x15 m. Topographic predictors such as curvature or topographic wetness index (TWI) were derived from two digital elevation models with a resolution of 5 and 25 m, respectively (Baltensweiler et al., 2020). As the climatic predictor, the 10-year average of growing degree days was derived from daily gridded maps between 1941 and 1950 interpolated with the Daymet software (Thornton et al., 1997) provided by the Land Change Science Unit at WSL (Birmensdorf, Switzerland). In addition, the Euclidean distance to the closest church was extracted from the SwissTLM3D (Swisstopo, 2023) as an indicator for anthropogenic influence, assuming the church acts as a proxy for the centre of a settlement. All predictors were calculated as the mean value per segment.

2.3.4. Additional sampling

After the RF model had been trained with the initial training data, additional training data was derived from the training areas to further

improve the classification and mitigate potential bias. Three sampling techniques were applied to collect 600 additional samples each, originating in equal shares from all biogeographical areas.

Active Learning (AL), was used to complement the initial training data set by iteratively adding training samples selected to minimise their number and maximise their impact on model performance (Tuia et al., 2011). For this study, segments with high classification uncertainty were selected to complement the initial training data (Crawford et al., 2013). Classification uncertainty was derived for each segment from the output of the RF model as the difference of the probability of the most probable and the second-most probable class (Scheffer et al., 2001). The lower this difference (also referred to as margin uncertainty; MU) is, the higher the respective classification uncertainty. Thus, in a first step, all segments with a MU equal to zero, i.e., the most and second-most probable classes were equally likely, were treated as potential samples for AL. A MU equal to zero can result from either two classes being predicted as relatively likely, or from many classes having low probability. In the first case, the classifier is quite sure that the actual class is one of the two predicted ones (i.e., probability close to 0.5), but the decision between the two classes is uncertain. In the second case, the classifier is unable to determine any favourite out of the 16 possible classes (i.e., probability close to 0.0625). Thus, in a second step, samples were prioritised for additional labelling based on the maximum probability (i.e., probability of the most probable class). To address the first case, half of the samples for labelling were selected from the potential samples ordered by decreasing maximum probability, while, for the second case, the other half of the samples were selected from the potential samples ordered by increasing maximum probability. By doing so, AL supports the RF model to refine the boundaries between the habitat classes. The AL procedure was repeated twice, 300 samples were selected each time.

Since AL focuses on providing additional labels for segments with high prediction uncertainty, segments with low prediction uncertainty are never selected for additional labelling. Hence, implicitly, this strategy assumes that these segments are classified correctly, which is, however, not necessarily the case. Thus, an alternative sampling technique was defined focusing on misclassified segments with low classification uncertainty (Error sampling; ES). For this purpose, in a first step, all segments with a MU > 0.2 (distinct difference between the most and second most probable class) were treated as potential samples for error sampling. Of these candidate samples, one misclassified segment per 2x2 km square was selected by visual interpretation and labelled correctly. For the selection, priority was given to misclassifications across TypoCH 1st level classes (e.g., grassland instead of forest or vice versa, see Table 2). In addition, it was ensured that misclassifications between different classes were considered. As for AL, two iterative sampling rounds were performed, where, in total, 600 misclassified segments were labelled correctly.

To assess and compare the impact of AL and ES, random sampling (RS) was the default sampling strategy. As for the other sampling strategies, 100 segments were randomly selected per biogeographical region after excluding all training segments and segments used for the accuracy assessment (see section 2.4).

2.4. Accuracy assessment

A probability sampling design (Stehman and Foody, 2019), in the form of a systematic grid, was applied to select the segments for the accuracy assessment. First, a regular grid of 2x2 km squares was generated across the training areas. Then, all segments that intersected with the corners and the centre of the squares were extracted. This resulted in 1,168 segments that were classified by visual image interpretation, of which two segments covered by clouds were excluded.

2.5. Comparison to current habitat distribution

The mapping results were compared to the current habitat

distribution in the training areas according to the 2023 Habitat Map of Switzerland (Price et al. 2023) by performing a Spatial Intersect using ArcGIS Pro (v3.4.0, ESRI, Redlands, CA) software. Areas classified to shadow were ignored and the open forest and closed forest classes combined to enable comparison. The total area of each habitat class according to the 1946 and the 2023 classification was also calculated.

3. Results

3.1. Spatial distribution and accuracies of the habitat classes

Fig. 3 illustrates the predicted small-scale distribution of the habitat classes for example map sections. Full maps can be found in Figs. S1-S8. The prediction for the Jura map section depicts widespread *Grasslands* intermixed with *Forest*, *Open Forest* and *Wetland* (Fig. 3, JU). A typical pattern in the Central Plateau is settlement areas (*Building*) surrounded by *Orchard* and *Cropland* (Fig. 3, CP1-CP3) or *Wetland* adjacent to *Running Water* (Fig. 3; CP2). The map section for the Western Central Alps (WCA) is characterised by a small-scale mixture of multiple habitat classes including *Vineyard* on the south-facing slope and *Forest* on the north-facing slope. In the map section of the Southern Alps (SA), *Building* and *Cropland* are dominant in the valley bottom, while *Forest* and *Vineyard* are intermixed on the slopes. The remote alpine map sections in the Northern and Eastern Central Alps (NA and ECA) are characterised by a transition from *Forest* and *Grassland* to *Rock/Scree* and *Ice/Snow* with increasing altitude.

The predicted large-scale distribution of the habitat classes varied with elevation and biogeographical area (Fig. 4). For the following habitat classes, the predicted proportions decreased with altitude (Fig. 4a): *Standing Water*, *Wetland*, *Hedge*, *Orchard*, *Vineyard*, *Cropland* and *Building*. *Grassland* and *Forest* reached highest proportions at intermediate elevations, while *Rock/Scree* and *Ice/Snow* were predicted to be dominated at highest elevations. The training area in the Jura reached the highest share of *Grassland* (48 %, Fig. 4b) and the second highest share of *Wetland*. *Orchard*, *Cropland* and *Wetland* were predicted to be mainly present in the Central Plateau. *Snow/Ice* and *Rock/Scree* were predominantly present in the three alpine training areas. *Forest* was predicted to cover at least a fifth of the area of all training areas with a maximum of 41 % for the Southern Alps. *Vineyard* was predicted to be present in the Western Central Alps and the Southern Alps.

While the predicted large and small-scale spatial patterns appear to be plausible, comparison to independent data shows that highest class-specific accuracies were reached for *Standing Water*, *Flowing Water*, *Ice/Snow* and *Forest*, for both Producer's and User's accuracies (PA and UA, respectively; Fig. 5). Particularly low PA (<0.4) was observed for *Open Forest* and *Orchard*. *Open Forest* was most often misclassified as *Forest*, while for *Orchard*, the main source of omission errors was *Grassland* (Fig. S9). The classes *Wetland*, *Hedge* and *Building* featured lowest UA, which was due to an overprediction of these classes. For *Wetland*, sources of both commission and omission errors were mainly the classes *Grassland* and *Cropland*, respectively, while for *Hedge* and *Building*, commission errors occurred with multiple classes (Fig. S9).

3.2. Comparison of the sampling strategies

When comparing with the independent data, overall accuracy was lowest for initial sampling (IS) and increased for all additional sampling strategies (Table 5). ES performed slightly better than AL, while RS achieved lowest overall accuracy. Combining all samples led to an increase in overall accuracy.

Although the comparison with the independent data did not reveal great differences in the overall accuracy of the three sampling strategies, the predictions sometimes differed substantially (Fig. 6). For all three example map sections, ES differed the most from the other sampling strategies. The first column shows an open forest area in the Jura. The IS led to many misclassifications, particularly regarding *Buildings*, which

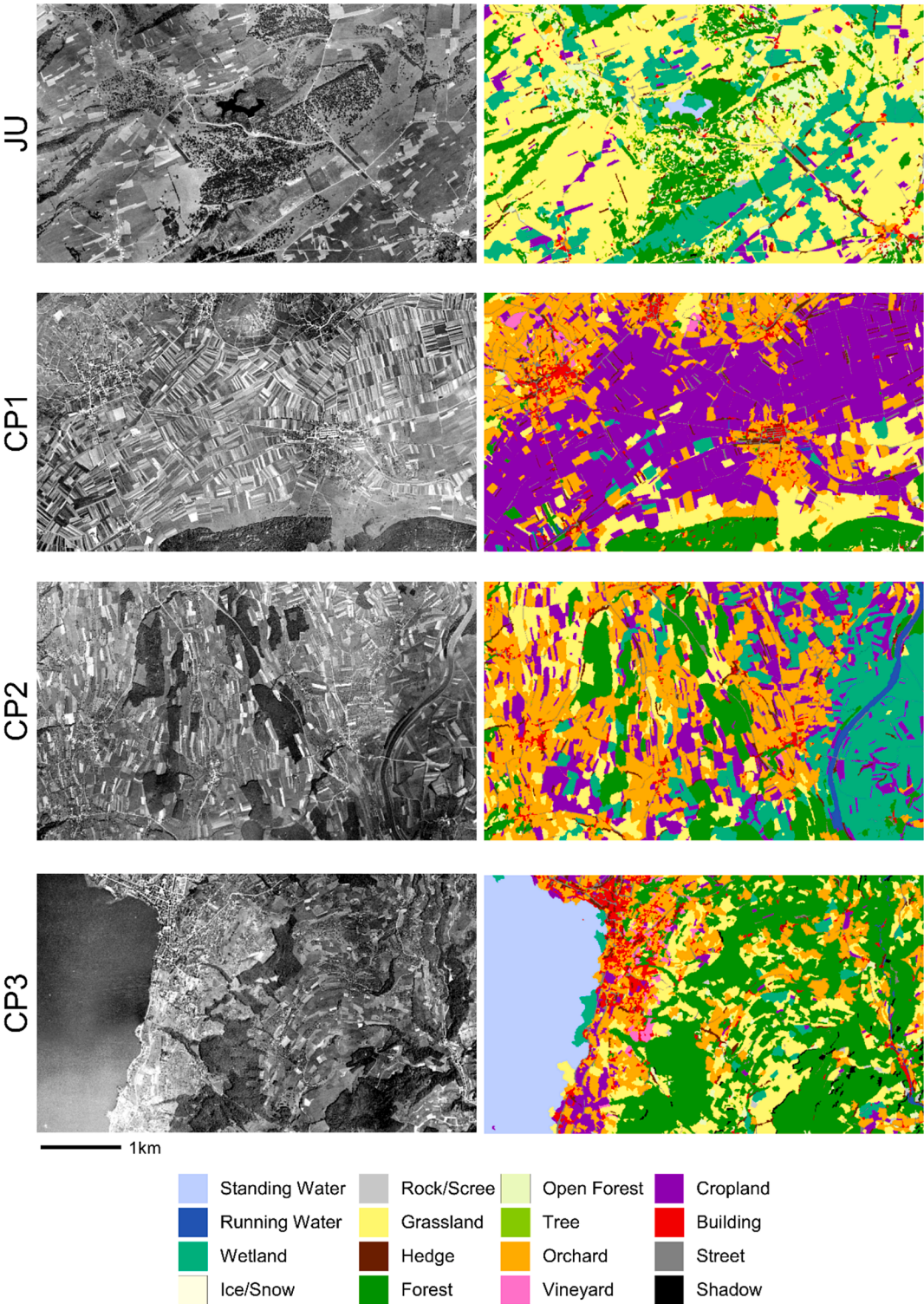


Fig. 3. B&W aerial orthoimage from 1946 (SWISSIMAGE HIST 1946 © swisstopo) and predicted habitat classes based on the model trained with all training samples for example map sections in the training areas (Table 1; JU: Jura; CP: Central Plateau; NA: Northern Alps; WCA: Western Central Alps; ECA: Eastern Central Alps; SA: Southern Alps). Remark: Segment borders are not displayed.

are not present in this area. AL could not resolve this issue because the segments classified as *Buildings* had a high MU (not shown), while *ES* improved the prediction substantially.

The second example represents a small village on the Plateau surrounded by *Orchards*, *Cropland* and *Wetland* towards the river in the west. This pattern is captured by all sampling strategies. The forest along

the river is however only partially mapped and confused with *Wetland*, although *ES* achieved the best result. *Cropland* is partially confused with *Orchards*.

The third example is from an alpine-nival area in the Western Central Alps. The class *Ice/Snow* is mapped well for all sampling strategies, while they differ regarding the transition between *Rock/Scree* and *Grassland*.

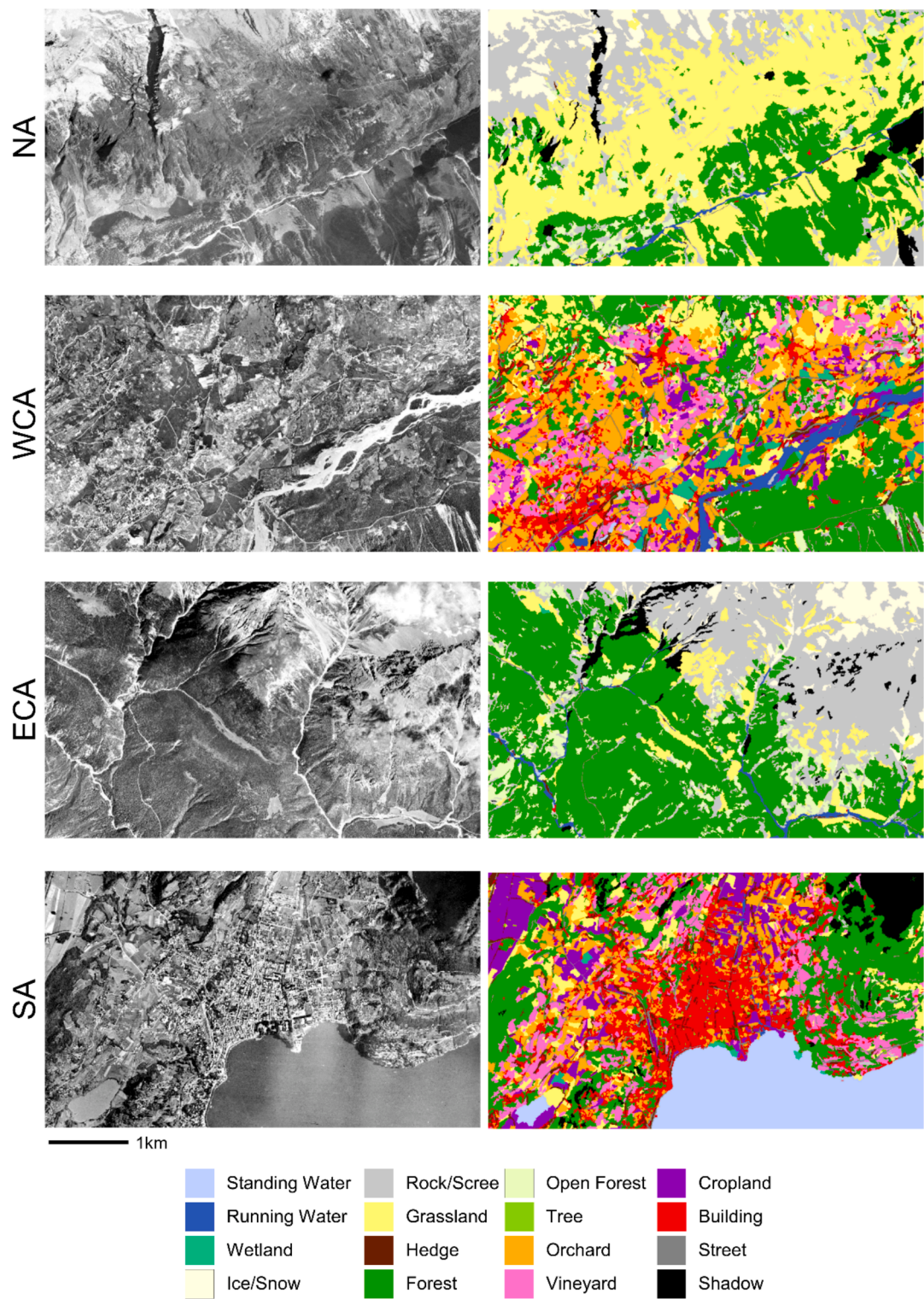


Fig. 3. (continued).

Several small segments were misclassified as *Tree*. This misclassification was least pronounced for ES.

3.3. Comparison to current habitat distribution

The comparison of the two maps showed that, summed across all training areas, the most stable of the habitat types were Standing water, Ice/Snow and Closed Forests with 99 %, 83.8 % and 74.1 % of their

mapped area remaining in those classes respectively. The least stable habitat classes were orchards, hedges and wetlands with less than 1 %, 4.5 % and 11.2 % of their area remaining in the same habitat class, and each of these classes transitioned mostly to grasslands and crops (Fig. 7). Table 6 demonstrates that within the training areas, a considerable increase in the area mapped as buildings, crop, grassland, hedges and shrubs and trees (outside forest) was observed as well as a strong decrease in the area of rocks and scree, wetlands and forest and an

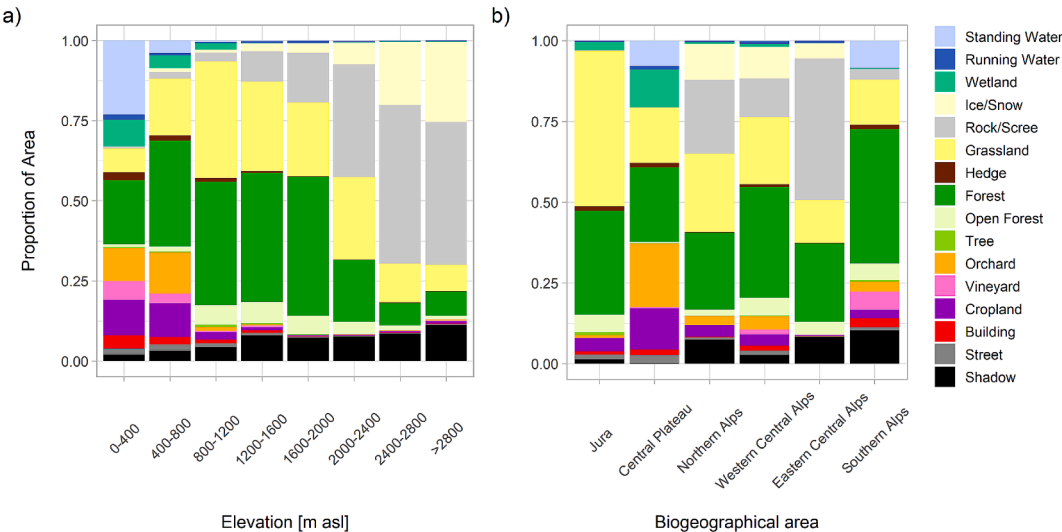


Fig. 4. Proportion of the predicted habitat classes a) along elevation and b) per biogeographical area predicted by the model trained with all training samples.

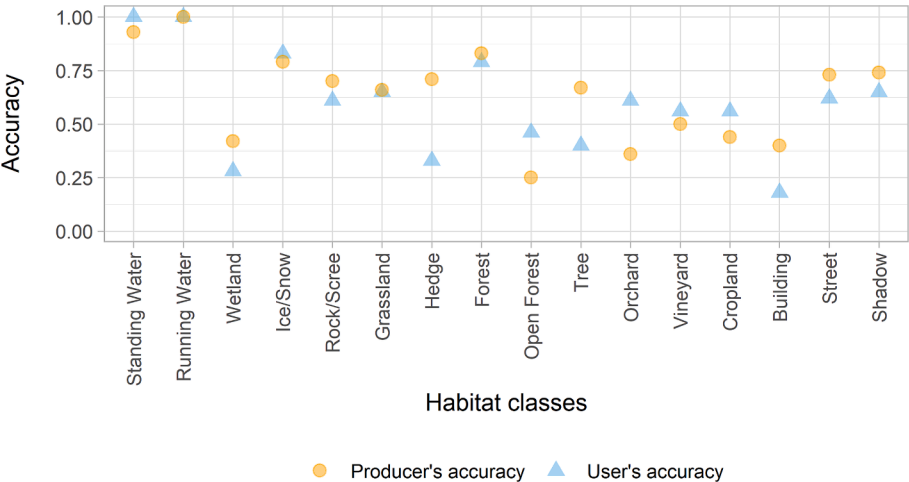


Fig. 5. Class-specific accuracies of the model trained with all training samples and across all training areas.

Table 5
Overall accuracies per sampling strategy.

Sampling strategy	Overall accuracy (95 % confidence interval)
Initial sampling (IS)	0.600 (0.571, 0.629)
Active learning (AL)	0.648 (0.620, 0.675)
Error sampling (ES)	0.661 (0.633, 0.689)
Random sampling (RS)	0.627 (0.599, 0.655)
All samples	0.678 (0.650, 0.705)

almost total loss of orchards.

4. Discussion

In this study, we demonstrated the feasibility of deriving an area-wide historical habitat map for Switzerland from historical aerial imagery with a machine learning and iterative sampling approach. Such a map would support the understanding of present biodiversity patterns and the identification of potential legacy effects and serve as a baseline for spatially explicit landscape and conservation planning. The method developed is applicable to a variety of training areas, representing the main biogeographical regions of Switzerland, without the need for region-specific adjustments. A relatively large number of habitat classes

(15) were mapped at high spatial resolution.

The results for the training areas showed that the region-specific spatial habitat patterns were represented well, considering both their large- and small-scale distributions. The class-specific accuracy assessment revealed highest accuracies for the classes *Standing Water*, *Flowing Water*, *Ice/Snow* and *Forest*, which are the habitat classes that appear the least complex and least susceptible to within class variations with respect to image tone and texture in black and white imagery. Lowest accuracies were observed for *Building*, *Open forest*, *Orchard* and *Hedge*, which can have similar tonal characteristics to each other, and complex shadow variations in black and white imagery making differentiation difficult (Manandhar et al. 2009). Wetland, which is difficult to distinguish from grassland and water classes due to low radiometric contrast in historical black and white imagery (Mboga et al. 2020) also had low classification accuracy. A large number of classes presents a challenge for accuracy assessments, as the number of independent samples per class is relatively low despite substantial classification efforts (Stehman and Foody, 2019). As more than a dozen habitat classes were distinguished, lower class-specific accuracies can be expected, than when classifying a smaller number of classes.

In line with other mapping studies based on B&W aerial imagery (e.g., Vogels et al., 2017, Lydersen and Collins, 2018), we applied geographic object-based image analysis. Our results show that the

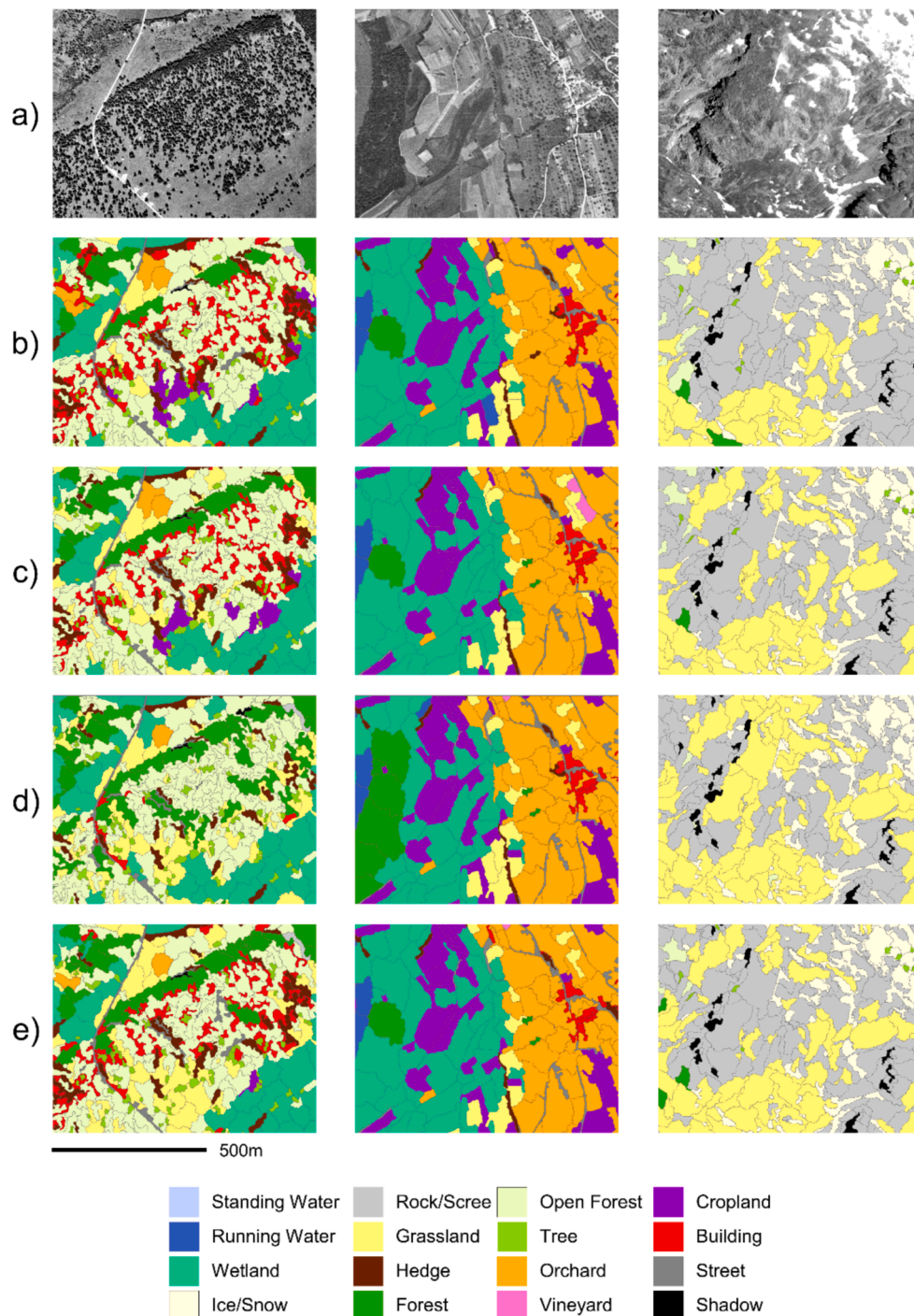


Fig. 6. Example map sections for three locations in the training areas (column 1: Jura; 2: Central Plateau 2, 3: Western Central Alps). a) B&W aerial orthoimage from 1946 (SWISSIMAGE HIST 1946 © swisstopo), predicted habitat classes based on the model trained with the b) initial training data (IS), c) initial training data and additional samples collected with active learning (AL), d) initial training data and additional samples collected with error sampling (ES), e) initial training data and additional samples collected with random sampling (RS).

segments generated were mostly meaningful for separating habitat classes and that segments covering more than one habitat class could usually be assigned to a dominant class. Nevertheless, it is a limitation of the study that habitat types that can be defined as fine scale elements such as trees, hedges and buildings are mapped using the same segmentation algorithm as habitats that are a mosaic of elements such as orchards and vineyards. The use of a multiscale segmentation might further improve the identification of these small landscape elements (e. g., Abbas et al., 2020), which are currently only partly identified.

While methods for sampling additional training data to increase the accuracy of initial classifications, such as AL (Tuia et al., 2011), are increasingly being developed (Li et al. 2024), they have not been widely used in remote sensing classification studies so far (but see for example Rüetschi et al., 2021), let alone studies applying object-based image analysis based on B&W aerial imagery. The results of this study indicate that such an approach can significantly increase the accuracy of object-based image classifications and that, of the sampling strategies used, AL and ES outperform RS. They further suggest that AL improves the

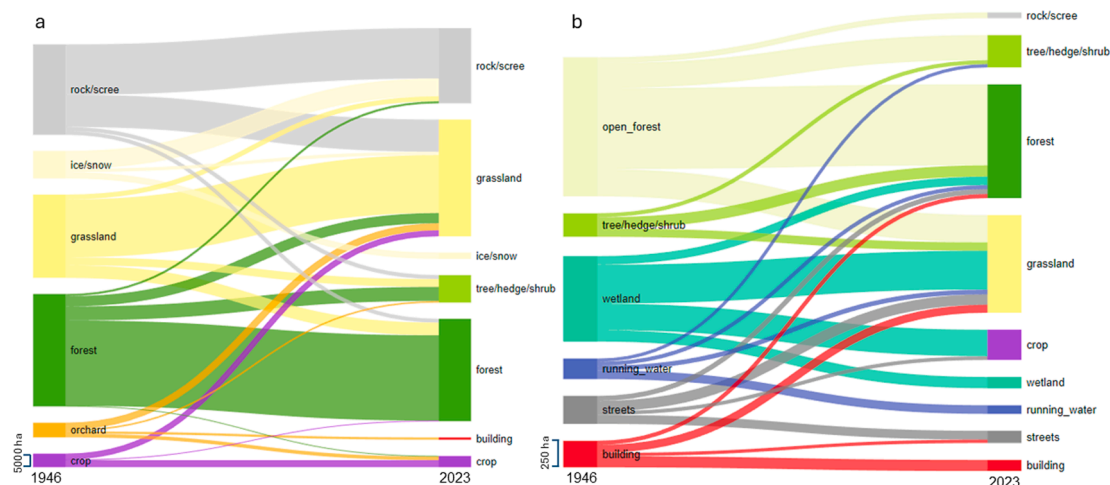


Fig. 7. Transitions between the habitat classes from the 1946 classification (left) to the 2023 classification (right) for readability the results are separated into a) larger area habitat classes (total area within the training areas greater than 5000 ha) and b) smaller area habitat classes. Transitions that were less than 10 % of the total area of a habitat class across all training areas, as well as standing water which was 99 % stable, are excluded from the graphic.

Table 6

Percentage of the total of the training areas mapped to each habitat class in the 1946 and 2023 classifications. Areas mapped as shadow from the 1946 images are excluded.

Habitat class	1946	2023
building	0.8 %	1.9 %
crop	4.0 %	4.4 %
forest	31.3 %	28.2 %
glacier/snow	7.0 %	1.7 %
grassland	23.3 %	30.9 %
hedge/shrub	0.6 %	6.4 %
orchard	4.5 %	0.1 %
rock/scree	22.7 %	18.6 %
running water	0.7 %	0.5 %
standing water	1.3 %	1.5 %
streets	0.9 %	1.4 %
tree	0.2 %	2.6 %
vineyard	0.5 %	0.8 %
wetland	2.4 %	1.1 %

delineation of related classes (e.g., *Forest* vs *Open forest*; or *Ice/Snow* vs *Rock/Scree*), but is not able to resolve classification issues where the model achieved low prediction uncertainty. This is not surprising, as segments to complement the initial training data were selected based on uncertainty. A clustering-based selection strategy for AL (Tuia et al., 2011) may be more promising in this case. Error sampling, as implemented in this study, represents a valuable complement to the AL strategy. However, in comparison to AL, error sampling requires more resources as misclassified segments need to be identified by either an interpreter or by comparison of the classification results with high-quality mapping equivalent to ground truth data, which is rarely available. We conclude that combining different sampling strategies for training data collection has the potential to improve the mapping, particularly in the case of multi-class classifications.

Overall, the method presented is suited to generating an area-covering habitat map for Switzerland based on the orthorectified composite of aerial photographs from 1946. Further research would allow optimisation of the classification and increase the usability of the map. Most importantly, increasing the variability of the training samples is expected to further improve the classification, particularly regarding the overprediction of the classes *Building*, the confusion of *Running Water* with *Street* in alpine areas or the distinction between *Forest*, *Open forest*, *Orchard* and *Grassland*. Although the distinction of 15 habitats classes is detailed in the context of classification of black and white imagery, the

broad classes limit the conclusions that can be made regarding the implications for biodiversity and also the comparisons that can be made to modern detailed mapping products and associated assessments of habitat change. Therefore, for some classes, the feasibility of a finer distinction of habitats should be evaluated. *Cropland* classification, which had the lowest reliability for training samples, could be improved by separation into parcel-based crop rotation areas and managed grassland, although the dynamic nature of these classes should be kept in mind for any multi-time step analyses. The class *Forest* could be further separated by dominant leaf type into broadleaved and coniferous, or by structural characteristics into dwarf shrubs, coppice stands, even-aged stands and old-growth forests. Such information is highly relevant for biodiversity conservation (Zeller et al. 2023) or could be used for spatially explicit historic growing stock estimations (Gschwantner et al. 2022). Forest management plans (Bürgi, 1999) or historical terrestrial photographs (Stockdale et al., 2015) could inform and support training data sampling. In the class *Grassland*, dry or alpine grasslands could likely be mapped individually (Kindermann et al., 2023), while in the class *Wetland*, it may be possible to further distinguish fens, raised bogs and wet meadows. Efforts regarding a finer distinction of the habitat classes would likely benefit from an extension of the predictor set. Potential candidates would be bedrock type (e.g., Essl et al. 2012) or additional bioclimatic predictors, such as a continentality index (e.g. Title and Bemmels, 2018). An alternative focus could be on improving the identification of specific habitat classes. For habitats featuring a characteristic spatial structure, such as for example *Vineyard*, *Orchard*, *Building* or *Tree*, Convolutional Neural Networks (CNNs) could be applied to segment and extract them directly from the B&W aerial images (Alam et al., 2021).

While the comparison between the mapping results of the 1946 and the 2023 habitat classification gives an interesting insight into broad degrees of change within Swiss landscapes, it is a major caveat of this work that the methodologies, input data and resulting accuracies for these two mapping products were vastly different. Therefore, care must be taken when interpreting these results. The increase in built area (building and streets) and the loss of orchards and areas of glaciers and permanent snow is a known phenomenon that is demonstrated in this comparison (Swiss Federal Statistical Office, 2021). However, the decrease in rock/scree areas and increase in grassland area could likely rather be attributed to different methodologies and better ability to detect low vegetation grassland in the current habitat map than to actual habitat change. Similarly, the current habitat map used aerial laser scanning data to map non forest trees, hedges and shrubs, thereby considerably increasing their detection rate over what was possible with

historical imagery. In order to make any reliable conclusions about habitat change, a version of the current habitat map using a methodology as similar as possible to the historical classification approach would be necessary.

5. Conclusions

Historical aerial photographs provide highly valuable information about the distribution and extent of habitats in the past. This information, together with knowledge of current habitat distribution, can contribute to understanding present biodiversity patterns, or observed biodiversity change, and potentially fighting extinction debt effects. In particular, historical imagery from the period before European landscapes began to change at an increasing rate, i.e., post second world war, can serve as baseline data. The method developed distinguishes more than a dozen habitat classes and is applicable to highly diverse environmental and cultural conditions without the need for region-specific adjustments. Overall, this study shows that comprehensive habitat-specific information can be extracted from historic B&W aerial imagery for large spatial extents and that different sampling strategies address diverging classification issues. We thus recommend combining multiple sampling strategies, i.e., active learning and error sampling, for mapping improvement instead of relying on one single strategy.

CRedit authorship contribution statement

Nica Huber: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Matthias Bürgi:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Christian Ginzler:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Birgit Eben:** Writing – review & editing, Validation, Investigation, Data curation. **Andri Baltensweiler:** Writing – review & editing, Writing – original draft, Resources, Data curation. **Bronwyn Price:** Writing – review & editing, Visualization, Project administration, Funding acquisition, Conceptualization.

Funding

This work was supported by the Swiss Federal Research Institute WSL's internal research grant program.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank all data providers, particularly the Swiss Federal Statistical Office, Josef Fischer from the Stiftung Reusstal and Stefan Rey from the canton of Zug for the provision of historical maps. Further, we thank Marius Rüetschi for sharing R code. We thank three anonymous reviewers and the editor for their constructive feedback which led to significant improvements to the manuscript.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jag.2025.104464>.

Data availability

Data will be made available on request.

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