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Grassland-use intensity maps for Switzerland based on satellite time series: Challenges and opportunities for ecological applications

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Using a recently developed rule-based algorithm, we mapped grassland-use intensities across Switzerland at a fine spatial resolution based on freely available satellite data with high accuracy. The resulting maps explained biodiversity patterns in Swiss grasslands well, demonstrating their great potential for diverse ecological applications and biodiversity research.

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Abstract

Land-use intensification in grassland ecosystems (i.e. increased mowing frequency, intensified grazing) has a strong negative effect on biodiversity and ecosystem services. However, accurate information on grassland-use intensity is difficult to acquire and restricted to the local or regional level. Recent studies have shown that mowing events can be mapped for large areas using satellite image time series. The transferability of such approaches, especially to mountain areas, has been little explored, however, and the relevance for ecological applications in biodiversity and conservation has hardly been investigated. Here, we used a rule-based algorithm to produce annual maps for 2018–2021 of grassland-management events, that is, mowing and/or grazing, for Switzerland using Sentinel-2 and Landsat 8 satellite data. We assessed the detection of management events based on independent reference data, which we acquired from daily time series of publicly available webcams that are widely distributed across Switzerland. We further examined the relationships between the generated grassland-use intensity measures and plant species richness and ecological indicator values derived from a nationwide field survey. The webcam-based verification for 2020 and 2021 revealed that most detected management events were actual mowing/grazing events (≥78%), but that a substantial number of events were not detected (up to 57%), particularly grazing events at higher elevations. We found lower plant species richness and higher mean ecological indicator values for nutrients and mowing tolerance with more frequent management events and those starting earlier in the year. A large proportion of the variance was explained by our use-intensity measures. Our findings therefore highlight that remotely assessed management events can characterise land-use intensity at fine spatial and temporal resolutions across broad scales and can explain plant biodiversity patterns in grasslands.

Introduction

Grasslands constitute valuable habitats with high biodiversity, are used for fodder production and livestock grazing and provide other key ecosystem services (Dengler et al., 2020). Land-use change affects these ecosystems in many ways (Schils et al., 2022). Intensification alters species composition and is a major driver of biodiversity loss (Allan et al., 2014). Frequent mowing, fertiliser input or intensive grazing lead to a shift towards more productive environmental conditions and greater competition for light (Eskelinen et al., 2022). This promotes more common and widespread species at the expense of specialist species, causing homogenization of communities (Gossner et al., 2016), which in turn negatively affects ecosystem multifunctionality (Soliveres, Manning, et al., 2016; Soliveres, van der Plas, et al., 2016). On the other hand, the abandonment of sites that are no longer economically valuable can lead to a complete loss of grassland ecosystems because of secondary succession towards shrubland or forest communities (Dengler & Tischew, 2018). This poses a particular threat to the remaining low-productive but ecologically valuable semi-natural grasslands. The species richness of plants is a biodiversity indicator that is often used to assess land-use effects. The intermediate disturbance hypothesis suggests that the highest plant species richness occurs at intermediate disturbance levels (Connell, 1978). Several studies have indicated that plant species richness is higher in non-intensively managed grasslands than in abandoned and intensively managed ones (Boch et al., 2018; Dengler & Tischew, 2018; Socher et al., 2012; Zechmeister et al., 2003). Therefore, to study spatial and temporal patterns of biodiversity, accurate and repeated information on land-use intensity is needed.

Recent studies have shown that the latest earth observation sensors facilitate the detection of annual grassland mowing events for large areas, due to their high spatial and temporal resolutions (Reinermann et al., 2020). Since a high temporal resolution is crucial for monitoring the intra-annual vegetation dynamics of grasslands, optical satellite time series from the Landsat and Sentinel-2 missions have been used in combination to increase the number of clear-sky observations (Griffiths et al., 2020; Schwieder et al., 2022). The integration of Sentinel-1 radar data has been suggested to overcome temporal gaps in optical time series caused by cloud cover (De Vroey et al., 2021; Komisarenko et al., 2022; Lobert et al., 2021). However, the relationship between radar data and mowing events appears to be much weaker, possibly leading to more false positives compared with optical satellite imagery (Reinermann et al., 2022).

Both rule-based (i.e. change detection using predefined thresholds) and machine-learning approaches were used to detect mowing events. For instance, in Germany, various studies used rule-based algorithms to generate nationwide annual maps of grassland-mowing frequency, all following a similar approach of identifying drops in a vegetation index within a time series (Griffiths et al., 2020; Reinermann et al., 2022; Schwieder et al., 2022). These and previous studies (e.g. Kolecka et al., 2018) highlighted that mowing can be mapped at large scales with simple and comprehensible rule sets for which no extensive model calibration is required. Alternatively, machine-learning approaches that do not rely on predefined thresholds have been investigated more recently (Komisarenko et al., 2022; Lange et al., 2022; Lobert et al., 2021). Even though machine learning might outperform rule-based algorithms in terms of accuracy, the comparability of different studies is challenging due to the dependency on various factors (e.g. management regimes, model calibration effort). Although promising machine-learning approaches have been presented, the limited availability of high-quality training data might hamper the transferability in space and time (Lange et al., 2022).

However, despite considerable progress in recent years, it has been suggested that further research is needed for large-scale applications and operational usability, especially because of the lack of suitable reference data to perform comprehensive validations (De Vroey et al., 2022). In addition, different landscape configurations, environmental conditions and management, but also satellite-data availability, have a large impact on the results and the transferability of the approaches to other areas. In particular, little attention has been given to the role of mixed management, grazing and abandonment (but see Watzig et al., 2023). Addressing the research needs described above is particularly important for large-scale applications and the implementation of pan-European products.

The majority of previous studies focused on remote-sensing data as such and the methodology, while the relevance of the derived maps for ecological applications in biodiversity and conservation has hardly been investigated (but see Hellwig et al., 2022). In ecological studies aiming to shed light on patterns of biodiversity and ecosystem functions in grasslands, land-use intensity information is among the most important explanatory variables (Allan et al., 2014; Blüthgen et al., 2012). However, gathering such fine-scale land-use information is laborious and cost-intensive (e.g. questionnaires), often spatially restricting such studies. Alternatively, proxies for land-use intensity such as mean ecological indicator values (e.g. nutrient and mowing tolerance values) or GIS variables that are hypothesized being related to land-use intensities (e.g. slope) are used (e.g. Roth et al., 2021). However, such proxies are often biased and might even lead to misinterpretations of the data (e.g. mean nitrogen indicator values are lowest at intermediate land-use intensities). This further highlights the need to develop cost-efficient methods using remote sensing to derive land-use intensity at large scales that can be used in various ecological studies. Mountain areas, which are common in Switzerland, seem to be well-suited model systems to test remote sensing-based land-use intensity estimates because both land-use abandonment and intensification are currently happening there at large scales. Previous studies in Switzerland using remote sensing have only been conducted on the regional scale (Giménez et al., 2017; Kolecka et al., 2018) or using Landsat data from 2015 (Stumpf et al., 2020) and have primarily been restricted to a single year of analysis.

The overarching aim of this study was to investigate the potential of remote sensing-based grassland-use intensity maps for ecological applications in mountainous environments with diverse management regimes. We used an existing rule-based algorithm (Schwieder et al., 2022) to produce annual (2018–2021) maps of grassland-management events, that is, mowing and/or grazing, for the whole of Switzerland using Sentinel-2 and Landsat 8 satellite data. We assessed the detection of management events based on independent reference data, which we acquired from daily time series of publicly available webcams that are widely distributed across Switzerland. Additionally, we investigated the ecological relevance of the generated intensity measures in relation to nationwide plant biodiversity data. On this basis, we addressed the following main questions:

1. **How reliably can grassland-use intensity be derived from satellite time series in a topographically challenging country with diverse management regimes?**
2. **Can remotely assessed management events help explain plant biodiversity patterns and environmental conditions?**

Data and Methods

Study area

Switzerland covers an area of 41 285 km^2, around 35% of which is used for agriculture, including alpine pastures. About 70% of these agricultural areas are permanent grasslands, of which around 36% are meadows, 17% are farm pastures and 47% are alpine pastures (Federal Statistical Office, 2021). Switzerland is characterized by a variety of environmental conditions and consists of six distinct biogeographical regions with strong differences in elevation, ranging from around 200 m to more than 4000 m a.s.l. in the high mountain areas of the Alps (Fig. 1). The productivity, length of the growing season and management systems of Swiss grasslands are therefore very diverse. Management of meadows and pastures is restricted to the main growing season, which lasts from about March to November at lower elevations, while it starts later and ends earlier at higher elevations. Meadows are mown one to six times a year, and a similarly large range in grazing intensity exists for pastures, in terms of livestock density and number of grazing periods. Mixed management comprising mowing and grazing is also common (Blüthgen et al., 2012; Boch et al., 2020).

Satellite data

All available Sentinel-2 Level 1C and Landsat 8 Collection 1 Tier 1 (C1 L1TP T1) satellite images acquired over Switzerland between 2018 and 2021 were processed into Level 2 products using FORCE v. 3.7, which includes radiometric, topographic and geometric corrections (Frantz, 2019). All satellite data were organized into a data cube structure of 30 × 30 km tiles and resampled to a spatial resolution of 10 m. The Sentinel-2 images were co-registered to improve the geometric alignment of the full time series (Rufin et al., 2020). Clouds, including a buffer of 300 m, and shadows and snow, including a buffer of 90 m, were masked out with the improved Fmask algorithm (Frantz et al., 2018; Zhu et al., 2015). For the total of 14 Sentinel-2 tiles (100 × 100 km per tile) and 8 Landsat 8 tiles (170 × 185 km per tile) covering Switzerland, around 2200 Sentinel-2 images and around 150 Landsat 8 images were annually available. An 80% cloud-cover threshold resulted, on average, in 63% and 47% retained Landsat and Sentinel-2 images, respectively, including the prerequisite of successful co-registration. The spatial and temporal patterns of the clear-sky observations (CSO) were mapped to analyse the potential influence of different data availabilities on the resulting maps. Finally, the enhanced vegetation index (EVI), which is suitable for monitoring the vegetation condition (Huete et al., 2002), was calculated for all corrected and clear-sky Sentinel-2 and Landsat 8 observations to produce a combined EVI time series.

Detection of grassland-management events and map creation

The rule-based algorithm described by Schwieder et al. (2022) was used for the detection of management events. We chose this approach because of its well-studied and solid performance for large-scale applications and its transferability to other areas without additional training. Furthermore, the algorithm was made easily accessible (https://github.com/davidfrantz/force-udf/tree/main/python/ts/mowingDetection) for the smooth integration into

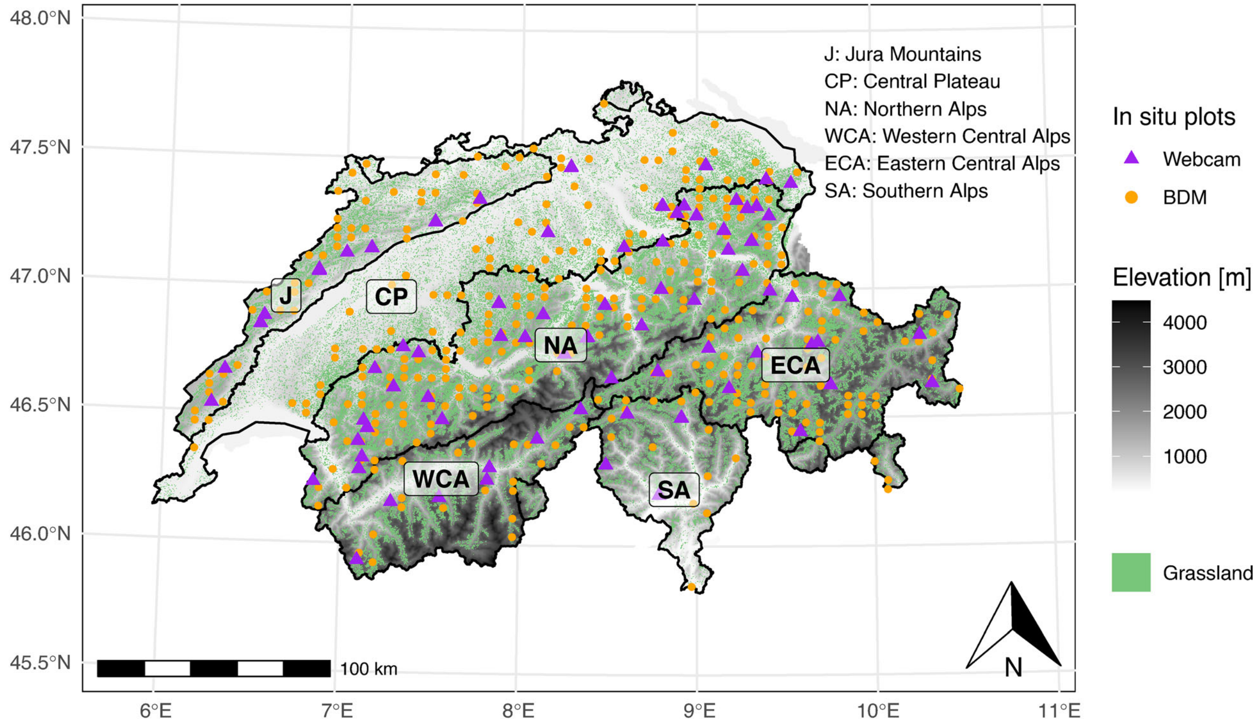

Figure 1. Grassland areas in Switzerland (Huber et al., 2022) stretch across six distinct biogeographical regions (Gonseth et al., 2001). Data from webcams and the Swiss Biodiversity Monitoring (BDM) programme were used for map verification and to investigate ecological relationships (©FOEN and swisstopo).

FORCE (Frantz, 2019) as a user-defined function (UDF). The algorithm searches for drops within a time series of a vegetation index (here EVI), which are related to a rapid decrease in biomass caused by mowing or grazing. Adaptive thresholds are automatically derived for each pixel based on the characteristics of the time series within a user-defined growing season (here 15 March to 1 November). A minimum interval between two consecutive management events was set to 15 days. Using the same parameter configuration as suggested by Schwieder et al. (2022), annual maps for 2018–2021 were generated, providing information on the number and timing of grassland-management events at a spatial resolution of 10 × 10 m for the whole of Switzerland. Finally, permanent grasslands were masked using a variety of land-use layers, according to Huber et al. (2022) but replacing the crop mask with the agricultural-use data from the cantons.

Reference data

Grassland management

Publicly available webcam images from the bergfex.ch archive (https://bergfex.ch/schweiz/webcams) were used to collect daily information on grassland management and to assess the accuracy of the management event detection. These webcams are mainly located in mountain areas, primarily for touristic purposes. One to three reference points were defined and georeferenced for each of the 82 webcams distributed across Switzerland, resulting in a total of 110 reference points (Fig. 1). Daily images from all reference points were visually interpreted for the years 2020 and 2021 and mowing/grazing events were recorded, always related to a defined image coordinate (Fig. 2). The occurrence of snow and manure was also noted. Grazing was observed for most of the reference points, often in combination with mowing. For 2020, a total of 152 individual mowing events and 179 grazing events were recorded. For 2021, 129 mowing and 153 grazing events were documented (Table 1). If two grazing events were not more than 10 days apart, these days and all in between were considered one event.

Agricultural production zones and land-use data

Existing geodata on agricultural production conditions and land use were used for the interpretation and validation of the overall spatial patterns of the remotely assessed intensity estimates. The Federal Office for

Figure 2. Examples of three webcams used to collect reference data on grassland management: Interpretation of two reference points on the same image and from some distance (left), observed grazing (middle) and mowing (right) from close to medium distance.

Table 1. Number of reference points and management events derived from the 82 webcams for the years 2020 and 2021.

Interpreted land-use type	Number of reference points		Number of mowing events		Number of grazing events	
	2020	2021	2020	2021	2020	2021
Mowing	16	22	35	48	–	–
Grazing	38	43	–	–	93	98
Mowing and grazing	51	37	117	81	86	55
No management	5	6	–	–	–	–
Total	110	108[a]	152	129	179	153

[a]In 2021, data from two webcams were not accessible.

Agriculture defines six agricultural production zones (lowland zone: LZ, hill zone: HZ, and four mountain zones: MZ 1–4) and one alpine summer pasture zone (PZ) based on climate, accessibility and topography (Federal Office for Agriculture, 2020). Land-use varies strongly among these zones, and direct payments are linked to zone-specific regulations. Biodiversity promotion areas (BPA) may not be mowed before 15 June in lower elevations (LZ, HZ), before 1 July in middle elevations (MZ 1 and MZ 2), and before 15 July in higher elevations (MZ 3 and MZ 4). Additionally, data on agricultural use collected by the cantons, as reported by the farmers, provided parcel-specific information for Switzerland for the year 2021. This data enabled the differentiation of intensive and extensive meadows and of pastures with and without biodiversity promotion.

Biodiversity and environmental data

The Swiss Biodiversity Monitoring (BDM) programme was established in 2001 with the goal of describing and monitoring biodiversity in Switzerland (https://www.biodiversitymonitoring.ch). It uses a regular grid which was determined randomly, and resurveys are conducted every 5 years (Koordinationsstelle BDM, 2014). Along with other species groups, the diversity of vascular plants is recorded in 1450 plots, each with an area of 10 m^2. For this study, only grassland plot data (discarding other habitat types) from the last complete 5-year cycle (2014–2018) was used. For the retained 364 plots (Fig. 1), the number of vascular plant species was extracted, and the mean ecological indicator values for nutrients and mowing tolerance were calculated for each plot (Landolt et al., 2010) using the programme Vegedaz (Küchler, 2019). Ecological indicator values describe the realised niche optimum of a species on an ordinal scale (Landolt et al., 2010). Values averaged over all species in a plot provide information on the environmental conditions of a site (Tölgyesi et al., 2014) and can be used for detecting ecological changes, for example, related to changes in land-use intensity (Boch et al., 2021; Diekmann, 2003).

Accuracy assessment

To assess how reliably management events were mapped, the pixel-based information from the maps was compared with the corresponding webcam-based references. This made it possible to quantify how often detected events matched actual events (precision; Eq. 1), how often actual events were missed (recall; Eq. 2), and the harmonic mean of those two measures (F1 score; Eq. 3).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1} = 2 \times \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{3}$$

In the webcam-based reference data, both mowing and grazing were considered management events, but they were also investigated separately. Detected management events within 10 days after or 2 days before mowing or grazing visible on the webcam images were accepted as true positives (TP), whereas all other detected events were considered false positives (FP). Conversely, non-detected events were registered as false negatives (FN). Some tolerance in temporal agreement was necessary because of gaps in the satellite time series and uncertainties in identifying the exact mowing/grazing day (e.g. due to fog) on the webcam images (Fig. 3).

Relationship with plant species richness and mean ecological indicator values

Simple and multiple linear regression models were calculated using the lm function in the R statistical software (R Core Team, 2022) to assess the relationships between grassland-use intensity and vascular plant species richness and the mean ecological indicator values for nutrients, which are commonly used to characterize differences in environmental conditions or habitat quality among sites (Boch et al., 2021; Pallett et al., 2016). The mean ecological indicator value for mowing tolerance was used as a third response variable; this indicator was expected to be positively correlated with mowing frequency and therefore suitable to test the functionality of the remote sensing-based management detection. The number and timing of management events from the map for the year 2020 were used as predictors (Table 2). To account for differences in spatial resolution and geometric accuracy between field and satellite data, the mean value from the map within a 30 m buffer around the field plot centre was used. As grassland management at the landscape level has been shown to be important for biodiversity aspects and multifunctionality (Neyret et al., 2021), the mean and standard deviation of management events at the landscape level (250 m buffer) were additionally included in the model. Within the same model, only predictor variables with low collinearity ($|r| < 0.7$) were used and model residuals were visually checked concerning the normality assumption. We have not included environmental factors (e.g. climate, topography) in our models to explicitly focus on remote sensing-based land-use intensity.

Results

Grassland-use intensity maps

Nationwide maps of grassland-use intensity, with information on the number and timing of individual management events, were generated at 10 m × 10 m spatial resolution for the years 2018–2021. Here, we focus on the results for 2020, for which reference data were available, but information on all other years can be found in the Figures S1 and S2; Tables S1–S4. The main spatial patterns that emerged are a higher grassland-use intensity with more management events (Fig. 4) and an earlier first management event of the year in the lowlands than in mountain areas (Fig. 5). The average across Switzerland was 1.5 management events for the year 2020, with the highest average value (2.8) occurring in the Central Plateau and the lowest (0.6) in the Southern Alps (Table 3). The first event occurred on 4 July (day of year [DOY] 186) on average across Switzerland; it took place substantially earlier in the Central Plateau (23 May [DOY 144]) and much later in the alpine regions (13 July [DOY 195] or later). There was some variation in the number and timing of management events between the years, but the overall patterns were largely consistent (Figs. S1 and S2), for example, with an average of 1.3–1.5 events per year (Tables S1–S4). In 2020, the average number of CSOs was 11.6 during the peak growing period (June to August),

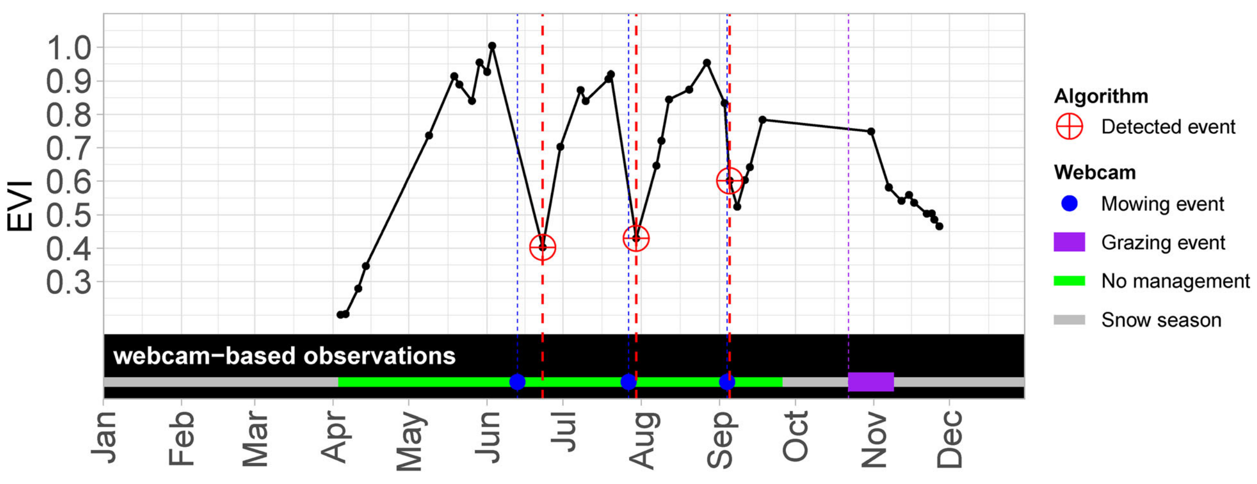

Figure 3. Example of the accuracy assessment:(top) an enhanced vegetation index (EVI) time series for 2020 with the detected management events (red circles and vertical lines) and (bottom) the corresponding webcam-based observations. In this example, all three detected events were actual events, but the last actual event (grazing) was not detected by the algorithm.

Table 2. Description of the predictor variables included in simple and multiple linear regressions.

Variable group	Predictor name	Description
Number of management events	N_plot	Mean number of management events on the plot level (buffer = 30 m)
	N_land	Mean number of management events on the landscape level (buffer = 250 m)
	N_SD_land	Standard deviation of management events on the landscape level (buffer = 250 m)
Timing of the first management event	T1_plot	Mean day of year of the first management event on the plot level (buffer = 30 m)
	T1_land	Mean day of year of the first management event on the landscape level (buffer = 250 m)
	T1_SD_land	Standard deviation of the first management event on the landscape level (buffer = 250 m)

meaning that, on average, one observation was available every eighth day unevenly distributed throughout the season (Table 3).

Map verification

Map verification was done individually for the years 2020 and 2021, using independent webcam-based management observations. For 2020, a precision of 78% was achieved, meaning that 156 of 199 management events detected by the algorithm were correct. The recall value for the same year was 47%, meaning that only 156 of 331 actual management events were detected. Slightly lower accuracies were achieved for the year 2021 (Table 4). Consequently, when considering all land-use types (i.e. mowing, grazing, mixed use), F1 scores were only in a moderate range of 59% for 2020 and 56% for 2021. The separate evaluation of the different land-use types revealed that the recall measure was strongly influenced by the omission of grazing events. The F1 scores were thus substantially higher for mowing (70% in 2020 and 69% in 2021) than mixed land use (63% in 2020 and 60% in 2021) and grazing (46% in 2020 and 42% in 2021). Further investigation revealed that the accuracy decreased towards higher elevation and that this was particularly due to the omission of grazing events.

Ecological application

Agricultural use and biodiversity promotion areas

The grassland-use intensity, described as the number of management events and the timing of the first management event in the year, reflected different agricultural production conditions. In productive zones, grasslands were mown/grazed earlier and more frequently (Fig. 6). Within these production zones, grassland-use intensity also differed substantially between the primary management types, with more and earlier management in meadows than in pastures. The difference between meadows with biodiversity promotion (BPA) and those without such status appeared to be more pronounced than that between meadows and pastures.

Plant species richness and mean ecological indicator values

In line with our expectations, we found lower plant species richness and higher mean ecological indicator values for nutrients and mowing tolerance with more frequent management events and events starting earlier in the year. The number of detected management events (N_plot) as a single predictor explained 26% of the variance in plant species richness (negative relationship), 49% of the mean nutrient indicator value (positive relationship) and 52% of the mean mowing tolerance indicator value (positive relationship; Table 5; Fig. S3). A similar proportion of the variance was explained by the timing of the first event (T1_plot) as a single predictor (Table 5; Fig. S3). These two main predictors (N_plot, T1_plot) were strongly correlated ($r = 0.80$) and therefore not used in combination. As additional predictors with low collinearity ($|r| < 0.7$), the variability (Standard deviation) on the landscape level in the number of events (N_SD_land) and in the timing of the first event (T1_SD_land) were used in separate models. At least one landscape measure was significant in each model. By including these landscape intensity measures, 2%–10% additional variance was explained, and this effect was strongest for the nutrient indicator value.

Discussion

In this study, grassland management events were mapped at a spatial resolution of 10×10 m for the whole of Switzerland for the years 2018–2021 using freely available satellite imagery and processing software. Based on a time series of daily webcam images, the accuracy of the approach was assessed, and uncertainties related to extensive management and grazing were highlighted. The derived maps made it possible to interpret the spatial and

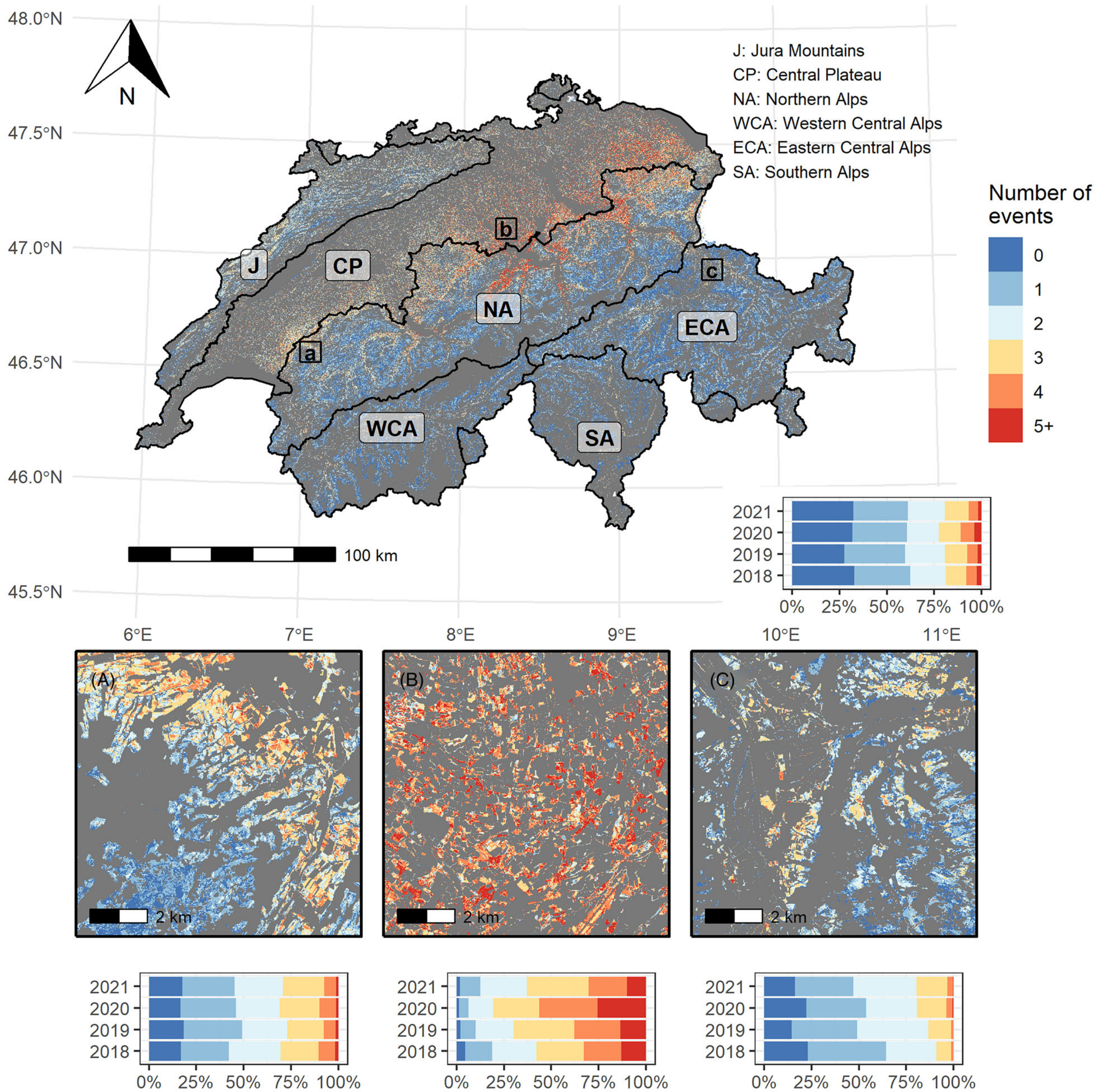

Figure 4. Spatial distribution of the number of management events in 2020 for Switzerland (top map) and for three zoomed-in regions (a–c). Horizontal bars in the graphs represent the area percentages for each year. The three zoomed-in regions show different grassland-use intensities, which are reflected in the distribution of management frequency.

temporal patterns of grassland-use intensity and to investigate their relationship with biodiversity variables/indicators. The remote-sensing-based intensity estimates reflected different production conditions and management practices and proved to be strong predictors of plant species richness and mean ecological indicator values.

Grassland-use intensity maps

The maps generated from remotely sensed data showed comprehensible spatial patterns of grassland-use intensity. More frequent management events and an earlier first event of the year were observed at lower elevations compared with values in the mountain areas (Figs. 4 and 5).

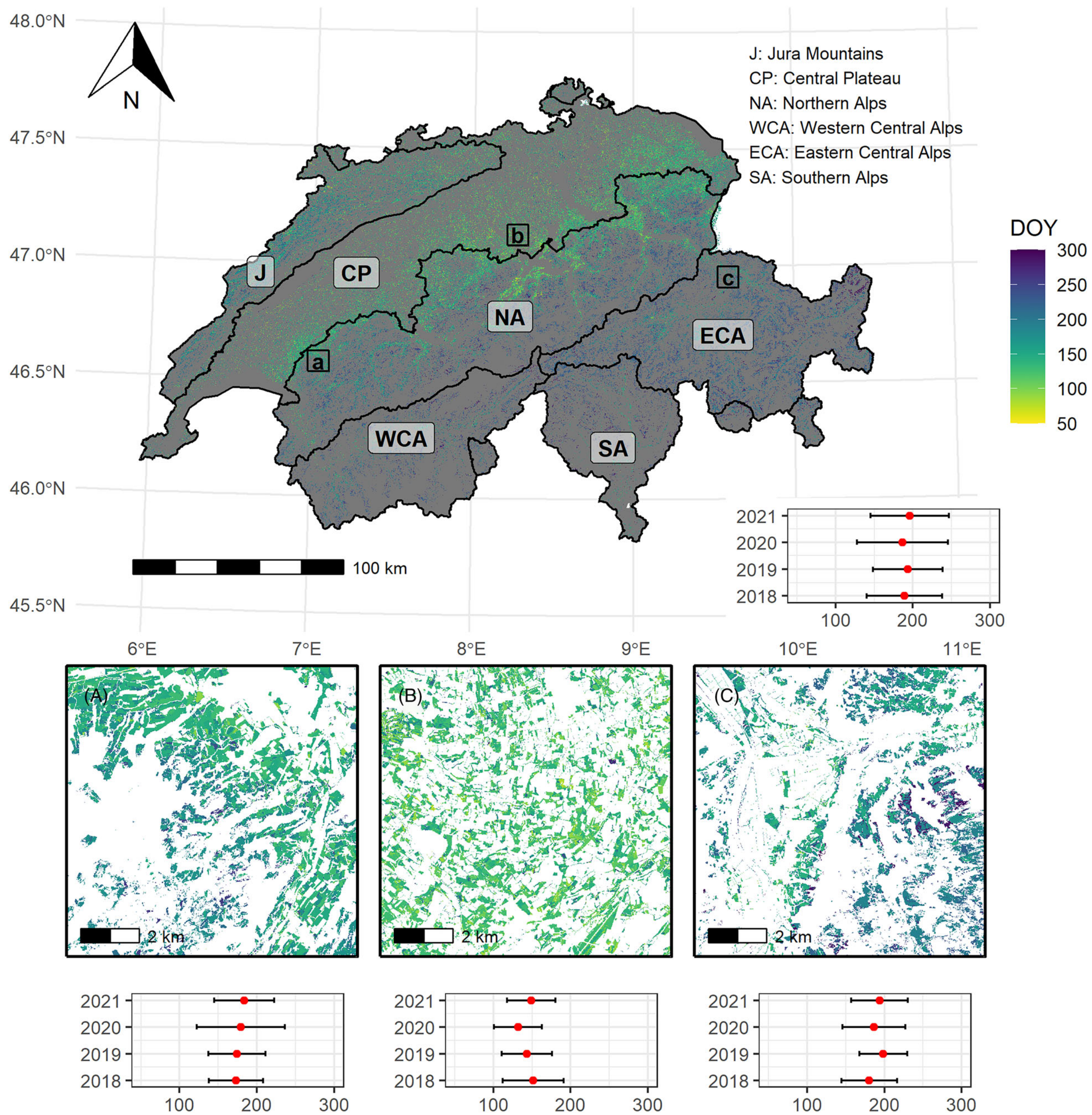

Figure 5. Spatial distribution of the timing (day of year; DOY) of the first management event in 2020 for Switzerland (top map) and for three zoomed-in regions (a–c). Circles and error bars in the graphs represent the mean and standard deviation for each year. The three zoomed-in regions show different grassland-use intensities, which are reflected in the timing of the first event of the year.

The overall spatial patterns were largely consistent for all 4 years (Figs. S1 and S2), with a similar grassland-use intensity per biogeographical region in different years (Tables S1–S4). This supports the robustness of the applied approach to varying meteorological conditions, which affect both vegetation growth and the availability of cloud-free satellite imagery (Schwieder et al., 2022). For the interpretation of the map, it is important to keep in mind that no distinction was made between mowing and grazing events. While other studies have been focused on mowing events only (De Vroey et al., 2022; Reinermann et al., 2022; Schwieder et al., 2022), here we also assessed the accuracy of the derived grassland-use intensity maps in grazed areas, which represent an important

Table 3. Distribution and mean number of annual management events across biogeographical regions and in total across Switzerland in 2020 as well as the mean day of year (DOY) of the first management event. The mean number of CSOs during the peak season (June–August) and the percentage of the area for which the algorithm did not return any results (processing error) are also given. The six biogeographical regions are Jura (J), Central Plateau (CP), Northern Alps (NA), Western Central Alps (WCA), Eastern Central Alps (ECA) and Southern Alps (SA).

	Area by number of management events in km^2 and %									
2020	0 events	1 event	2 events	3 events	4 events	≥5 events	Mean no. events (SD)	Mean DOY first event (SD)	Mean CSO Jun–Aug (SD)	Processing error in %
J	176.3 (16.3%)	376.2 (34.9%)	333.1 (30.9%)	147.0 (13.6%)	37.9 (3.5%)	8.7 (0.8%)	1.6 (1.1)	170.1 (41.4)	9.0 (3.1)	0.0%
CP	113.4 (5.2%)	291.5 (13.4%)	516.7 (23.8%)	566.8 (26.1%)	422.1 (19.5%)	259.3 (12%)	2.8 (1.4)	143.7 (38.7)	14.9 (4.6)	0.0%
NA	1221.4 (28.8%)	1329.6 (31.4%)	661.7 (15.6%)	500.1 (11.8%)	341.1 (8%)	183.2 (4.3%)	1.5 (1.5)	195.8 (64)	12.7 (5.6)	0.1%
WCA	545.9 (53.6%)	341.5 (33.6%)	94.9 (9.3%)	26.3 (2.6%)	6.6 (0.6%)	2.4 (0.2%)	0.6 (0.8)	234 (51.5)	11.2 (4.8)	0.5%
ECA	1212.6 (51.3%)	763.1 (32.3%)	285.7 (12.1%)	83.0 (3.5%)	16.8 (0.7%)	2.1 (0.1%)	0.7 (0.9)	217.8 (36.5)	8.8 (3.8)	0.2%
SA	451.7 (55.4%)	257.3 (31.5%)	73.9 (9.1%)	24.4 (3%)	6.7 (0.8%)	2.0 (0.2%)	0.6 (0.9)	230.0 (48.3)	9.9 (4.8)	0.2%
Total	3721.3 (31.9%)	3359.2 (28.8%)	1966.0 (16.8%)	1347.7 (11.5%)	831.2 (7.1%)	457.7 (3.9%)	1.5 (1.5)	186.4 (59)	11.6 (5.2)	0.1%

management regime across European grasslands. The accuracy assessment revealed a lower mapping accuracy for grazing than for mowing, particularly at higher elevations (Table 4), and indicated that the number of management events is likely underestimated in higher-elevation areas that are primarily grazed (discussed in the following section). Our results support the conclusions of previous studies (De Vroey et al., 2022; Reinermann et al., 2022) that the distinction between meadows and pastures is important when mapping grassland-use intensities, though strongly limited by the availability of high-quality reference data. The extensive data collected in the context of this study could be used to further investigate the separation of meadows, pastures and mixed uses, for example, to test novel remote-sensing approaches.

Algorithm performance and suggestions for improvements

With 613 management events recorded over a 2-year period based on more than 100 independent webcam-based reference points, the accuracies achieved here are in line with those reported by Schwieder et al. (2022), highlighting the transferability of the approach. Accordingly, we observed that the accuracy for pastures and areas with mixed uses was lower than for mowed meadows (Table 4). This was particularly the case for grasslands at higher elevations, which are generally less productive and less intensively used. Visual inspection of such time series confirmed that extensive use and grazing in particular often had little to no influence on the vegetation index in such areas. This is an important finding that underscores that extensive use of low-productive grasslands and abandonment are difficult to distinguish. While grazing and extensive management, in general, was still detected to some extent, further refinements of the algorithm are needed for such areas, especially to reduce omission errors. Extensive use of grassland typically results in less biomass removal, which means that the change in vegetation index is less pronounced than for intensively managed grassland. The use of additional thresholds, the inclusion of spatial context information, or the detection of non-abrupt changes in the phenological profile might be useful to improve the algorithm for such areas. In general, information on phenology could be useful to account for different season lengths and reduce out-of-season misclassifications. In addition, we observed that the vegetation index frequently decreased over two consecutive observations after mowing, which is probably because the mown grass can remain on the grassland for several days after cutting. Therefore, our results support the findings of Kolecka et al. (2018) that the integration of the second-to-last observation into the

Table 4. Verification using independent webcam-based management observations for 2020 and 2021. Verification was conducted for all plots, for different land-use types (mowing, grazing, mixed use) and three elevation groups. Plots without observed management (5 in 2020 and 6 in 2021) were not assessed as a separate group.

		Year 2020				Year 2021			
Land-use type	Elevation zone (m.a.s.l)	No. plots	F1 score	Precision	Recall	No. plots	F1 score	Precision	Recall
All	<1000	23	68%	88%	55%	21	72%	88%	61%
	1000–1500	48	59%	76%	48%	48	58%	87%	43%
	>1500	39	44%	65%	33%	39	28%	47%	20%
	All plots	110	59%	78%	47%	108	56%	79%	43%
Mowing	<1000	4	67%	89%	53%	6	71%	80%	63%
	1000–1500	8	75%	75%	75%	11	81%	85%	77%
	>1500	4	57%	67%	50%	5	18%	25%	14%
	All mowing	16	70%	79%	63%	22	69%	77%	62%
Grazing	<1000	2	78%	100%	64%	5	74%	87%	65%
	1000–1500	13	38%	55%	29%	15	31%	88%	19%
	>1500	23	45%	67%	34%	23	32%	59%	22%
	All grazing	38	46%	66%	35%	43	42%	75%	29%
Mixed use	<1000	17	67%	87%	54%	10	71%	93%	58%
	1000–1500	27	64%	85%	51%	22	60%	87%	45%
	>1500	7	41%	86%	27%	5	27%	50%	19%
	All mixed use	51	63%	86%	50%	37	60%	86%	46%

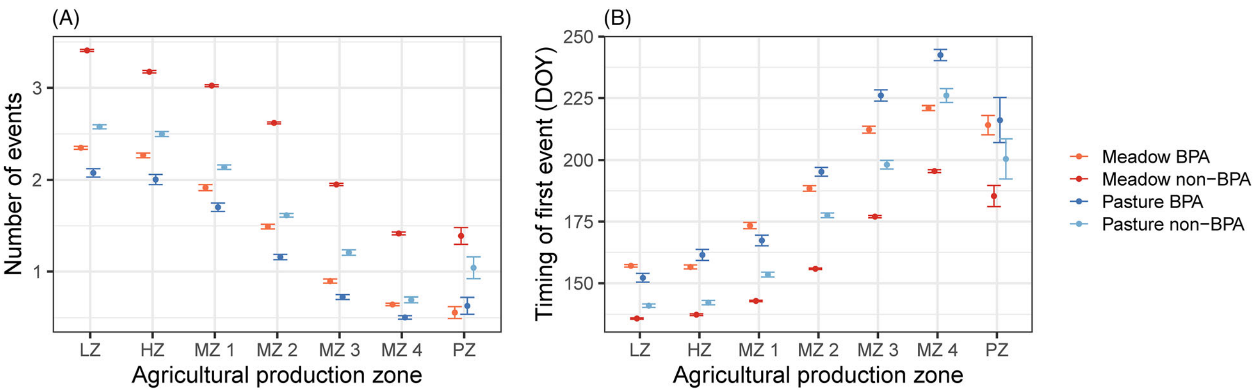

Figure 6. Mean number of management events (A) and mean day of year (DOY) of the first management event (B) per agricultural production zone and use type for the year 2020 (n = 100 000 random samples). Agricultural production zones from high to low productivity: lowland zone (LZ), hill zone (HZ), mountain zones (MZ 1–4) and alpine summer pasture zone (PZ) (Federal Office for Agriculture, 2020).

ruleset should be considered. Examples of the accuracy assessment showing the EVI time series, detected and observed management events are provided in Figure S4. Among them is an example (S4-C) that illustrates the general applicability of the algorithm for intensively used pastures.

The assessed accuracy was slightly lower for 2021 than for 2020, probably because of the smaller number of CSOs. A high frequency of CSOs has been found to be crucial to achieve low omission errors, as vegetation typically recovers quickly after a management event, with the vegetation index often reaching a value similar to that before the management event within 2 weeks (Kolecka et al., 2018; Reinermann et al., 2022). A small number of CSOs could lead to a systematic underestimation of management events, which might be particularly problematic for mountainous regions, due to more snow, clouds and topographic shadows, and for areas without overlapping Sentinel-2 orbits. To mitigate this effect, we followed the suggestions of Griffiths et al. (2020) and Schwieder et al. (2022) to integrate Landsat 8 data, which indeed led to a substantially larger number of CSOs (Fig. S5). However, the coarser spatial resolution of Landsat 8 also results in a larger amount of mixed pixel information,

Table 5. Linear regression outputs for models with a single and multiple predictors, including either the number of management events or the timing of the first management event. For variable explanations, see Table 2.

	Plant species richness		Mean nutrient indicator value		Mean mowing tolerance value	
	Estimate	*P*	Estimate	*P*	Estimate	*P*
No. events only						
Intercept	44.23	<0.001	2.56	<0.001	2.30	<0.001
N_plot	−5.21	<0.001	0.33	<0.001	0.38	<0.001
R2	26%		49%		52%	
Timing only						
Intercept	10.69	<0.001	4.64	<0.001	4.74	<0.001
T1_plot	0.13	<0.001	−0.01	<0.001	−0.01	<0.001
R2	25%		49%		51%	
Full model with no. events						
Intercept	45.24	<0.001	2.03	<0.001	1.87	<0.001
N_plot	−3.99	<0.001	0.25	<0.001	0.31	<0.001
N_SD_land	−7.57	<0.01	0.42	<0.001	0.38	<0.01
T1_SD_land	0.11	<0.05	0.01	<0.001	0.01	<0.01
R2	27%		56%		56%	
Full model with timing						
Intercept	23.42	<0.001	3.79	<0.001	3.95	<0.001
T1_plot	0.09	<0.001	−0.01	<0.001	−0.01	<0.001
N_SD_land	−9.39	<0.01	0.32	<0.001	0.32	<0.01
T1_SD_land	–	>0.1	0.01	<0.001	0.01	<0.001
R2	28%		58%		56%	

which might be critical for areas where small parcel structures are dominant. Here, the additional use of high-resolution imagery could be beneficial; for example, the integration of PlanetScope imagery showed very promising results in a preliminary test (data not shown). Moreover, several studies have indicated that the integration of radar data can be beneficial (Komisarenko et al., 2022; Lobert et al., 2021). Still, radar data are influenced by several environmental factors, such as rain and (soil) moisture, and are usually noisy due to speckle effects, which might be especially challenging for small grassland parcels in mountainous areas.

The webcams used for verification in this study were mainly located in mountain areas. The accuracy might be higher at lower elevations and for more productive grasslands because changes in the vegetation index are larger in these areas, as mentioned above. The locations of our reference points were intentionally chosen to be in the centre of the parcels. Consequently, small parcels, parcel edges or (generally speaking) mixed pixels would be expected to have greater uncertainties (Kolecka et al., 2018). The effective map accuracy therefore could not be assessed, because doing so would require a probability sampling design for the reference data (Stehman & Foody, 2019).

Applications for ecology and conservation

Our findings of lower plant species richness and higher mean ecological indicator values for nutrients and mowing tolerance with more frequent management events and events starting earlier in the year are in line with our expectations based on results from previous field-based studies. For instance, in the Biodiversity Exploratories programme, fine-scale land-use intensity information was gathered in three regions of Germany using laborious and cost-intensive questionnaires targeting farmers (Blüthgen et al., 2012). Based on this land-use data, it has been clearly demonstrated that increasing land-use intensity is causing declines in biodiversity (including plant species richness; Allan et al., 2014; Socher et al., 2012) and altering abiotic and environmental factors, as reflected by higher mean ecological indicator values for nutrients (Blüthgen et al., 2012). However, very small-scale questionnaire-based information on land-use intensity spatially restricts studies, highlighting the need to develop cost-efficient methods using remote sensing to derive land-use intensity at large scales, for example, for countries or even whole biomes.

Our models explained almost 30% of the variance in plant species richness and 60% of the variance of the mean ecological indicator values using only remote sensing-based information on grassland management. Predicting species richness and comparable biodiversity indicators is complex and the predictive power of ecological models is often in a comparable range (Boch et al., 2021; Klimek et al., 2007; Zellweger et al., 2015). With the integration of additional environmental variables, more variance could probably be explained (Weber et al., 2018), but we intentionally kept it as simple as possible, also because management and environmental conditions are usually closely linked and difficult to disentangle. We are aware that the high rate of omission errors in extensively used pastures introduces some uncertainty in the interpretation of our models and probably reduces the percentage of explained variance. However, this needs further analyses and simulation with a larger dataset in future studies.

Apart from studies focusing on mowing detection, the usefulness of remote-sensing data for predicting grassland-use intensity (Lange et al., 2022), plant biomass and species richness (Muro et al., 2022) using neural networks has been demonstrated. Both studies showed promising results but also indicated difficulties in spatial transferability because of the small extent of the training data. Our findings highlight the robustness of the rule-based approach applied here and indicate that remotely assessed management events can be used to explain plant biodiversity patterns and to characterise environmental conditions at larger scales. In addition, we were able to demonstrate the added value of land-use intensity at the landscape level. This area-wide information provides another level of spatial detail for ecological modelling approaches that can be used to support decision-makers in developing and assessing nature conservation frameworks.

Conclusions

In this study, we analysed dense time series of freely available optical remote sensing data in combination with a rule-based algorithm, which enabled us to estimate the annual intensity of grassland use across the whole of Switzerland for the first time. The derived maps confirmed anticipated spatial patterns of grassland-use intensities, demonstrating that the algorithm can be transferred to mountainous regions. We validated the resulting intensity estimates with a large set of independent reference data derived from webcam images. The algorithm led to robust estimations for different environmental conditions and varying data availability. Further research is needed to optimise the approach for the exact discrimination between extensively used meadows, pastures and abandoned areas, where we observed the largest uncertainties. We further identified limitations at high elevations and in regions with sparse data situations due to single orbits, clouds and extended periods of snow cover, areas where the inclusion of additional remote sensing data is promising for future research. Our findings support the value of large-scale grassland-use intensity estimates for ecological applications, as they helped explain patterns of plant species richness and environmental conditions. The approach can likely be transferred to other temperate grasslands and mountainous regions for detecting management events and exploring changes in biodiversity patterns related to land-use intensity. The maps generated in this study are freely accessible to practitioners and scientists under the following repository: https://doi.org/10.16904/envidat.428.

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Author Contributions

DW, CG and SB conceived the ideas and designed methodology; DW, TK, SB and LK collected and prepared the data; DW analysed the data; DW, SB and MS led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data Availability Statement

Should the manuscript be accepted, the maps will be made freely accessible under EnviDat (https://www.envidat.ch), the open data repository of the authors' institute, which ensures unified and managed access to research data. We will provide the direct link to the data for the final version of the manuscript.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Spatial distribution of the number of management events for the years 2018–2021 for Switzerland and for three zoomed-in regions (a, b, c). The three zoomed-in regions show different grassland-use intensities, which are reflected in the distribution of management frequency.

Figure S2. Spatial distribution of the timing (day of year; DOY) of the first management event for the years 2018–2021 for Switzerland and for three zoomed-in regions (a, b, c). The three zoomed-in regions show different grassland-use intensities, which are reflected in the timing of the first event of the year.

Figure S3. Linear relationship between the number and timing of management events with plant species richness (top row), nutrient indicator (middle row) and mowing tolerance indicator values (bottom row).

Figure S4. Examples of the accuracy assessment showing the enhanced vegetation index (EVI) time series for 2020 with the detected management events and the corresponding webcam-based observations: (A) both actual mowing events were detected, (B) all three actual mowing events were detected and three grazing events later in the season were missed, (C) four of seven actual grazing events were detected, (D) only one of four actual grazing events was detected.

Figure S5. Number of clear-sky observations (CSO) between June and August for all four years, with only Sentinel-2 (left) and with Sentinel-2 and Landsat 8 observations (right).

Table S1. Distribution and mean number of annual management events across biogeographical regions and in total across Switzerland in 2018, as well as the mean day of year (DOY) of the first management event.

Table S2. Distribution and mean number of annual management events across biogeographical regions and in total across Switzerland in 2019, as well as the mean day of year (DOY) of the first management event.

Table S3. Distribution and mean number of annual management events across biogeographical regions and in total across Switzerland in 2020, as well as the mean day of year (DOY) of the first management event.

Table S4. Distribution and mean number of annual management events across biogeographical regions and in total across Switzerland in 2021, as well as the mean day of year (DOY) of the first management event.

