Ecological Indicators xxx (xxxx) xxx-xxx

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: http://ees.elsevier.com

Spatial monitoring of grassland management using multi-temporal satellite imagery

Felix Stumpf [a,b,*], Manuel K. Schneider [a], Armin Keller [a], Andreas Mayr [c], Tobias Rentschler [d], Reto G. Meuli [a], Michael Schaepman [a], Frank Liebisch [a,e]

[a] Agroscope, Reckenholzstrasse 191, Zurich 8046, Switzerland
[b] Department of Geography, Remote Sensing Laboratories (RSL), University of Zurich, Winterthurerstrasse 190, Zurich 8057, Switzerland
[c] Institute of Geography, University of Innsbruck, Innrain 52, Innsbruck 6020, Austria
[d] Department of Geosciences, Chair of Soil Science and Geomorphology, University of Tübingen, Rümelinstraße 19-23, Tübingen 72070, Germany
[e] Department of Environmental Systems Science, Institute of Agricultural Sciences, ETH Zurich, Universitätstrasse 2, Zurich 8092, Switzerland

ARTICLE INFO

Keywords
Grassland management
Spatial monitoring
Spectral time series
Management practice
Mowing
Grazing
Use intensity

ABSTRACT

Spatial monitoring of grassland management is crucial for ecosystem assessment and the establishment of sustainable agriculture. Switzerland is covered by large areas of small structured grassland parcels differing in management practices and use intensities, making the mapping of grassland management challenging. We present a monitoring tool to map grassland management, distinguishing between mowing- and grazing practice, and between different use intensities for Swiss agroecosystems. By analyzing pixelwise spectral time series of 2015, derived from satellite imagery of the Landsat archive, we estimated the number of management events and biomass productivity. Both estimates were used to map classes of dominant management practices and use intensities following a stepwise clustering approach. The grassland management (GM) classes were evaluated relative to established spectral and topographical patterns of grassland use intensity, and in terms of spatial conformity with available regional land use data. The GM classes were also analyzed with respect to management related vegetation plot data on species diversity, as well as on indicator values for nutrient supply and management tolerance. The stepwise clustering gave three use intensity classes for each dominant management practice of grazing (pasture) and mowing (meadow). Use intensity was higher for meadows than pastures with a distinct intensity gradient for each grassland practice. The GM classes reproduced established spectral and topographical patterns of grassland use intensity, indicated by increased standard deviations (SD) of spectral time series profiles (e.g. mean SD of 0.048 for pastures and 0.054 for meadows) and lower slopes (e.g. mean slopes of 10° for pastures and 7° for meadows). The averaged spatial conformity of the GM classes with a cantonal land use map was 82% for meadows and 97% for pastures. The GM classes spatially matched with land use patterns of three subregions, e.g. with an areal proportion of 73% pasture classes for a subregion dominated by grazing. Moreover, the GM classes reproduced established vegetation patterns of grassland use intensity along the GM intensity gradient, showing a mean decrease in species richness (33%), as well as a mean increase in indicator values for nutrient supply (5%), grazing tolerance (4%), and mowing tolerance (6%).

1. Introduction

More than a third of the agricultural area in Europe is covered by grasslands, widely being subject to land use intensification (O‘Mara, 2012; Smit et al., 2008). Grassland agroecosystems, as grazed pastures or mown meadows, provide most of the fodder required by ruminant livestock to meet the growing demand for animal-derived food (Allen et al., 2011; Oenema et al., 2014; Orr et al., 2016). Grasslands also provide key ecosystem services related to soil quality, hydrological balance, and climate change (Askari and Holden, 2014; Isselstein and Kayser, 2014; Soussana and Lemaire, 2014). Moreover, temperate grasslands in Europe are rich in biodiversity, which is recognized as the foundation for ecosystem functioning (Cardinale et al., 2012; Kleijn et al., 2011; Wilson et al., 2012). For example, ~18% of the endemic vascular plant species in Europe are bound to grassland habitats (Habel et al., 2013).

Grassland management (GM) largely determines the capacity of the agroecosystem to provide ecosystem services (Power, 2010; Rodríguez et al., 2006). GM mainly involves practices such as grazing and mowing in various combinations and use intensities (Giménez et al., 2017; Peeters et al., 2014). The term ‘use intensity’ often refers to the frequency of management practices and alongside, to the amounts of mineral or organic fertilizer inputs, which determines biomass productivity (Hudewenz et al., 2012; Rose and

* Corresponding author at: Agroscope, Reckenholzstrasse 191, 8046 Zürich, Switzerland.
E-mail address: felix.stumpf@agroscope.admin.ch (F. Stumpf)

https://doi.org/10.1016/j.ecolind.2020.106201
Received 8 January 2019; Received in revised form 4 Febraury 2020; Accepted 6 Febraury 2020
Available online xxx
1470-160/

Leuschner, 2012). Use intensity depends on the environmental setting related to terrain conditions, growth period, water supply, soil nutrient levels, and plant species compositions (Kizeková et al., 2018; Mottet et al., 2006; Tasser and Tappeiner, 2002), and often adversely affects ecosystem services (Foley et al., 2011; Porqueddu et al. 2016; Soussana and Lemaire, 2014). Rose et al. (2012) found that higher mowing intensity decreased groundwater recharge. Zhou et al. (2017) demonstrated that higher grazing intensity significantly increased the loss of carbon and nitrogen in the soil. Moreover, higher use intensity is associated with biodiversity declines, often accompanied by landscape homogenization (Allan et al., 2014; Foley et al., 2011; Gossner et al., 2016).

The large extents of agricultural grasslands, combined with the adverse effects of land use intensification on ecosystem services and biodiversity, outline the need for sustainable GM systems (Huyghe et al., 2014; Simons and Weisser, 2017; Tälle et al., 2016). This is in line with European agricultural policies, such as the Common Agricultural Policy of the European Union (CAP) and the Swiss Agricultural Policy (SAP; EC, 2018; FOAG, 2018). A key measure of these policies comprises payments linked to management practices and use intensities that promote ecosystem services and the conservation of biodiversity (Henle et al., 2008; Kleijn and Sutherland, 2003). However, ecological benefits in terms of reduced greenhouse gas emissions and biodiversity conservation seem to be limited in Switzerland (Kleijn et al., 2006; Knop et al., 2006; Leifeld and Fuhrer, 2005). Moreover, it has recently been claimed that CAP measures, intended to preserve ecosystem services and halt biodiversity declines in the European Union, are inefficient (Kleijn et al., 2011; Pe'er et al., 2014; Pywell et al., 2012).

Current efforts to establish sustainable grassland management systems include the development of monitoring tools to derive detailed spatial and temporal information on management practices and use intensities (Nagendra et al., 2013; Zaks and Kucharik, 2011). Spectral time series from space-borne imagery allow progressing phenological stages to be detected, which in turn allows vegetation trends and GM to be mapped (Ali et al., 2016; Kennedy et al., 2014; Svoray et al., 2013). However, spatial and temporal resolutions of spectral imagery are often inadequate to capture small-structured landscapes with diverse GM (Giménez et al., 2017; Li et al., 2017; Zhu et al. 2012). Moreover, the spatio-temporal availability of spectral data is often constrained by sparse data records and high monetary expenses (Asam et al., 2015; Kolecka et al., 2018; Sakowska et al., 2016).

With this study we contribute to the establishment of a sustainable GM system for Switzerland at a national scale. The objective is the development of a monitoring tool for annually mapping the management practice (mowing vs. grazing) and use intensity of small-structured grassland systems. Exemplarily, the tool is applied and evaluated for the year 2015.

The methodological framework is based on a spatial estimation of the management frequency and biomass productivity using pixelwise time series from multi-temporal satellite imagery. Both variables are used for a stepwise classification and clustering approach to derive GM classes, which describe the use intensity for areas dominated by grazing and mowing, respectively. The GM classes are evaluated by a statistical comparison with established spectral and topographical patterns of grassland use intensity. The GM classes are also evaluated by analyzing their spatial conformity with regional land use data, available for the entire canton of Berne and for three subregions with characteristic GM. In addition, the GM classes were analyzed with respect to management related vegetation plot data on species diversity, as well as bioindicators for nutrient supply and management tolerance.

2. Materials and methods

2.1. Study area

Switzerland covers an area of 41,000 km^2. The altitude varies between 196 m and 4634 m (a.s.l.). Total annual precipitation is ~500–2000 mm and the monthly mean temperature ranges from 1 °C in January to 17 °C in July (MeteoSwiss, 2018a,b). The Swiss agroecosystem covers 10,000 km^2 and is small-structured with a mean farm size of about 20 ha. Approximately 70% of the agricultural land is managed grassland, of which 12% is temporary grassland in rotation with other crops that is typically managed intensively. The majority of the managed grasslands are permanent pastures and meadows (SFSO, 2018; Stumpf et al., 2018). Most intensive grassland farming in Switzerland occurs in a band of moderate climate and suitable topography, running from southwest to the northeast of the northern half of the country (Leifeld et al., 2005; Price et al., 2015). With increasing elevations towards the alpine foothills in the south and the Jura uplands in the north, extensive grassland farming becomes dominant (SFSO, 2018). The study area demarcates the agricultural grassland area <1400 m (a.s.l.) in 2015, which covered ~5400 km^2 (Fig. 1; Stumpf et al., 2018).

2.2. Data base

2.2.1. Spectral time series data

Spectral time series for the study area were acquired from all available scenes of the optical satellite sensors Landsat ETM + and Landsat OLI in 2015.

Both sensors record a blue, a green, a red (RED), a near-infrared band (NIR), as well as two shortwave-infrared bands at a spatial resolution of 30 m × 30 m. Each scene was corrected to surface reflectance according to the Landsat Ecosystem Disturbance Adaptive Processing System (Schmidt et al., 2013). All pixels covered by clouds, cloud shadows, water, and snow were masked according to the CFmask algorithm (Zhu et al., 2015). Corrupted pixels, defined by at least one 'NoData' score in the spectral bands, were also removed (Stumpf et al., 2018). The Normalized Difference Vegetation Index (NDVI; Eq. (1); Rouse et al., 1974) was calculated for each scene, serving as a proxy for plant biomass (Liu et al., 2017; Schweiger et al., 2015; Weber et al., 2018).

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

The NDVI data were aggregated to a stack of median composite images, which establish pixelwise and spatially harmonized time series. The time series aggregation was optimized to cover as much of the growth period and study area as possible, and to provide an accurate temporal match between the composite periods and vegetation status. Accordingly, the most adequate time series stack was selected from a pool of iteratively aggregated time series stacks following the optimization criteria i) temporal extent and resolution, ii) balanced time step intervals and composite periods, and iii) spatial coverage. Moreover, time series with more than three missing values or with at least two consecutive missing values were excluded from the analysis. Missing values for the remaining time series were imputed using cubic spline interpolation (Wolberg and Alfy, 1999). The final NDVI time series ran from 16 March to 24 September of 2015 in 14 time steps, with composite periods between 3 and 9 days, time step intervals between 5 and 13 days, and a grassland area coverage of 89% (Figs. 1 and 2). The scenes were selected and processed using the computing platform Google Earth Engine API (Gorelick et al., 2017). Data aggregation for the final NDVI time series and imputation of missing values was

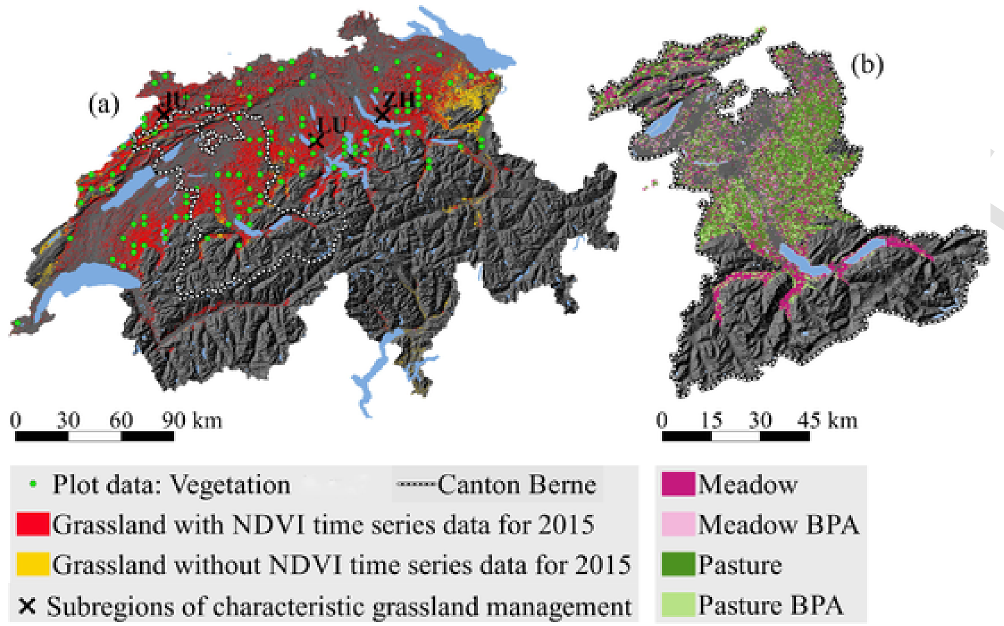

Fig. 1. Territory of Switzerland (a) with managed grasslands < 1400 m a.s.l. (red + yellow) and the territory of the canton of Berne (b) with official data on grassland use ('NDVI': Normalized Differenced Vegetation Index; 'BPA': Biodiversity Promotion Area, see Section 2.2.3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

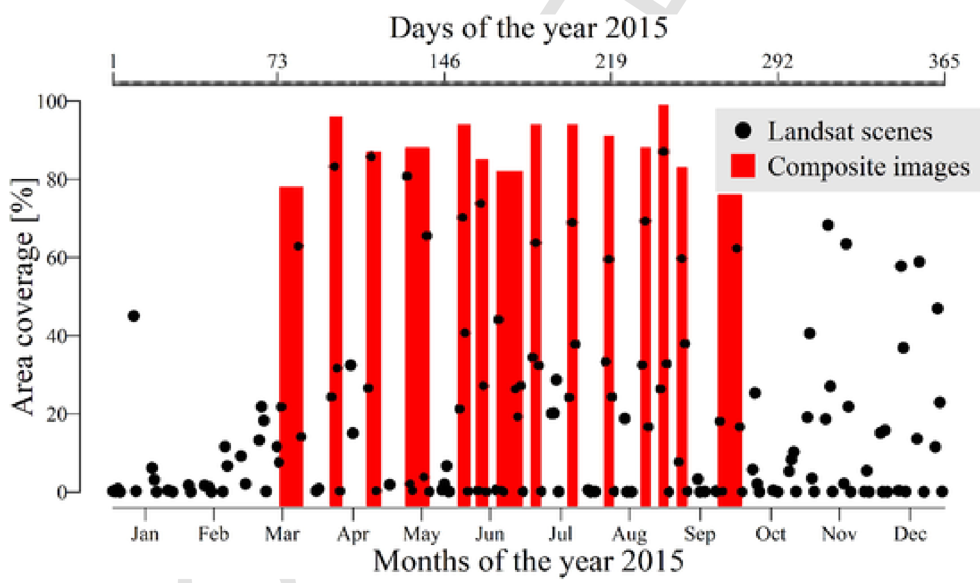

Fig. 2. Available Landsat scenes (sensors: ETM + and OLI) for the Swiss grassland area in 2015 (black dots), aggregated to a time series of composite images (red bars), and the areal coverage of the composite images relative to the total grassland area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

processed using the R-packages "zoo" and "raster" (Hijmans et al., 2017; Zeileis et al., 2018).

2.2.2. Terrain data

We acquired a digital elevation model (Elev) and derived the slope (Slope) with a spatial resolution of 25 m × 25 m. The elevation model is based on interpolating digitized terrain elements and contains mean errors of 1.5–3 m (SwissTopo, 2018). The slope was calculated according to the algorithm by Horn (1981), which applies 3 × 3 pixel window and is particularly suitable for rough surfaces. The terrain grids were resampled based on bilinear interpolation to a raster cell size of 30 m × 30 m to fit the spatial resolution and extent of the spectral time series data. Terrain data were processed using the R-packages "raster" and "base" (Hijmans et al., 2017; R Core Team, 2016; Table 1).

2.2.3. Cantonal grassland use data

We obtained georeferenced grassland use data, which determine the payment of agricultural subsidies for the canton of Berne for 2015 (Fig. 1; LANAT, 2018). The data include two classes of conventional grassland use ('Meadow' and 'Pasture'; see Fig. 1) and two classes of biodiversity promotion areas ('Meadow BPA' and 'Pasture BPA'; see Fig. 1). These land use classes are defined in terms of management practices related to grazing and mowing, as well as related to the application of farmyard manure and plant protection agents. The Meadow class represents land subject to at least one mowing event without further restrictions. The Meadow BPA class contains land subject to at least

Table 1
Summary statistics for the terrain variables elevation and slope (Min: Minimum; Q1: 25%-quartile; Q3: 75%-quartile; Max: Maximum; SD: Standard deviation).

	Min	Q1	Median	Mean	Q3	Max	SD
Elevation (Elev) [m]	388	556	693	712	840	1400	191
Slope [°]	0	4.1	8.2	9.6	13.6	33.5	6.9

one mowing event after 15 June, 1 July, or 15 July, depending on elevation and associated growth period. While grazing is permitted after 1 September, the application of farmyard manure and plant protection agents is prohibited. The Pasture class is confined to grazing as dominant management practice without further restrictions. The Pasture BPA class represents land dominated by grazing, while the application of manure and plant protection agents is prohibited. All land use units < 1 ha were excluded for the analysis to ensure a match with the spatial resolution of the spectral and terrain data (Table 2; AGRIDEA, 2018, SFA, 2018).

2.2.4. Subregional grassland use data

We also compiled semi-quantitative management information for three contrasting grassland-dominated subregions in the cantons of Lucerne, Zurich, and Jura based on the Swiss National Farm Census and other published data. Each subregion was randomly selected within the cantons of interest, covering a total area of 2.3 km^2 × 2.3 km^2 of which at least 50% are managed grasslands. The Swiss National Farm Census is the main instrument for administering direct payment schemes from the Swiss Federal Agency for Agriculture and includes annual data on livestock units (LSU) at farm level (AGIS, 2017; FOAG, 2018; Gärtner et al., 2013). In the Swiss context, LSU indicates use intensity of animal farming systems, since it is related to management practices such as grazing and mowing frequencies and organic fertilizer inputs (FOAG, 2018; Giménez et al., 2017). The livestock density index, defined as the ratio of livestock units to grassland area, was calculated using the livestock data for the farms in each subregion and served as indicator for use intensity. The mean mowing frequency and dominant management practice for each subregion were determined from published data. The grassland of the subregion in Lucerne (LU) is predominantly managed by intensive mowing and high application rates of farmyard manure (Liebisch, 2011). Grassland management of the subregion in Zurich (ZU) is characterized by mowing and grazing in varying intensities, and by different manure application rates (Giménez et al., 2017). Grasslands in the subregion of Jura (JU) are predominantly managed by grazing in low to moderate intensities (Table 3; Fig. 1; Chételat et al., 2013; Masé, 2005).

2.2.5. Vegetation data

We acquired vegetation plot data on species occurrence from the Swiss Biodiversity Monitoring Network (BDM), which spans

Table 2
Summary area statistics for the grassland use units of the canton of Berne according to grassland management classes in 2015 (Min: Minimum; Q1: 25%-quartile; Q3: 75%-quartile; Max: Maximum; SD: Standard deviation; BPA: Biodiversity promotion area).

	Min	Q1	Median	Mean	Q3	Max	SD	Total
Meadow [ha]	1	1.3	1.8	2.3	2.7	33.1	1.7	40,702
Meadow BPA [ha]	1	1.1	1.4	1.6	1.8	21.9	1	3933
Pasture [ha]	1	1.3	1.7	2.4	2.6	40.5	2.1	20,659
Pasture BPA [ha]	1	1.3	1.7	2.4	2.6	22.5	1.9	5723

Table 3
Grassland management characterization of subregions in the cantons Lucerne (LU), Zurich (ZU), and Jura (JU) in terms of the dominant practice, mowing frequency in 2014, and the livestock density index in 2015 (LSU: livestock unit).

	Dominant practice [–]	Mowing frequency [–]	Livestock density index [LSU*ha-1]
LU	Mowing	>5	1.87
ZU	Mowing/Grazing	2–5	1.36
JU	Grazing	–	0.94

a 6 km × 4 km sampling grid across Switzerland (BDM, 2014, 2017). Data were obtained at circular plots of 10 m^2 around the grid intersections (±5 cm) between 20 July and 20 September in 2012 to 2015. We identified a total of 120 sample plots that intersected spatially with the study area (Fig. 1).

The vegetation data is based on recording each identifiable vascular plant species within the sample plot. The data set includes species richness (SR) and the Landolt N indicator, which is similar to Ellenberg's nutrient indicator but adapted for the Swiss biogeography (Ellenberg, 1974; Landolt et al., 2010). Landolt N values are an ordinally scaled quantification of the species nutrient preferences, ranging from 1 to 5 with a higher value indicating an increased nutrient supply (Diekmann, 2003; Landolt et al., 2010; Pauler et al., 2019). The plotwise unweighted mean of the Landolt values ($N_{Landolt}$) indicates the site specific nutrient availability or soil fertility (Bartelheimer and Poschlod, 2016; Duprè et al., 2010; Klaus et al., 2012). Based on the species record, we also calculated the unweighted mean indicator values for grassland utilization according to Briemle et al. (2002), indicating tolerance for mowing ($MT_{Brie.}$) and grazing ($GT_{Brie.}$). Values of $MT_{Brie.}$ and $GT_{Brie.}$ range between 1 and 9, corresponding to the range from least to most tolerant for mowing and grazing, respectively (Briemle et al., 2002; Moog et al., 2002).

2.3. Spatial monitoring of grassland management

2.3.1. Mapping management practice and use intensity

Grassland use intensity was spatially quantified from the pixelwise NDVI time series (see Section 2.2.1), described by the management frequency (M_{freq}) and biomass productivity (BP). NDVI changes of a specific time series were used as local proxy for fluctuations in biomass (Flynn et al., 2008; Gao et al., 2013; Jiang et al., 2014). A loss of biomass greater than a threshold value q was deemed to be land use induced, and therefore identified as a management event (Kennedy et al., 2010; Sulla-Menashe et al., 2014). Based on the probability density function of all NDVI changes across the time series, q was specified for the probability $p = 0.01$ using the quantile-function of the R-package "stats" (Hyndman and Fan, 1996; R Core Team, 2016). Subsequently, M_{freq} was defined as the count of management events for each time series, while BP was defined as the accumulated absolute NDVI changes in the management events (Eq. (2) and (3)).

$$M_{freq} = \sum_{i=1}^{K} \left[\left(NDVI_{i+1} - NDVI_i \right) > q \right] \tag{2}$$

$$BP = \sum_{i=1}^{K} \left| \left(NDVI_{i+1} - NDVI_i \right) \left[\left(NDVI_{i+1} - NDVI_i \right) > q \right] \right| \tag{3}$$

where K is the time series ($i = 1,2,\ldots,13$), $NDVI$ is the NDVI value (Eq. (1)), and q is the threshold to ensure human interference for a biomass loss ($q = 0.02$). The variables M_{freq} and BP were calculated using the R-package "base" and "stats" (R Core Team, 2016).

We mapped GM classes as a combination of dominant management practice (grazing vs. mowing) and use intensity, applying a stepwise classification and clustering approach based on M_{freq} and BP. First, the study area was sub-divided into three initial grassland classes using the categorization of use intensity for Swiss grassland, $M_{freq} <= 2$, $3 <= M_{freq} <= 4$, and $M_{freq} >= 5$ (PRIF, 2017). Second, unsupervised K_{means} clustering for each initial grassland class was performed using BP to identify areas dominated by grazing and mowing. Grazing areas are characterized by low BP values and gradually changing NDVI profiles, while mowing areas show higher BP values and abrupt changes in the NDVI profile (Dusseux et al., 2014a, b; Fang et al., 2015; Taugourdeau et al., 2013; Weber et al., 2018). Therefore, the six GM classes were intended to describe gradual changes in use intensity for areas dominated by grazing ("$Pasture_{low}$", "$Pasture_{moderate}$", "$Pasture_{high}$"), and for areas dominated by mowing ("$Meadow_{low}$", "$Meadow_{moderate}$", "$Meadow_{high}$"). The Kmeans clustering was performed using the Hartigan-Wong implementation of the R-package "stats" (Hartigan and Wong, 1979; R Core Team, 2016).

2.3.2. Evaluation of grassland management classes

The adequacy of the estimated GM classes was assessed using different approaches and independent datasets.

First, we evaluated the GM classes by considering the statistical conformity with established change patterns of NDVI profiles for grassland. Meadows are predominantly characterized by bimodal NDVI profiles and increased BP values compared to pastures with mainly unimodal profiles. High intensity grasslands have bimodal NDVI profiles with increased variability, M_{freq}, and BP compared to lower intensity grasslands with flattened or unimodal NDVI profiles (Dusseux et al., 2014b; Estel et al., 2015; Taugourdeau et al., 2013; Weber et al., 2018). We compared the GM classes based on the mean NDVI profile changes for each class, and based on the absolute NDVI profile changes from a randomly selected location within each class. Descriptive statistics, M_{freq}, and BP were used as comparative measures.

Second, we evaluated the GM classes in relation to topographical conditions, which largely determine use intensity of grasslands. Increasing elevation is related to decreasing mean temperature, and therefore to a shorter growth period, which involves a decrease in use intensity (Lamarque et al., 2011; Weber et al., 2018; Zeeman et al., 2010). Similarly, increasing slope is related to decreasing use intensity, because of constraints on access for mowing machinery and livestock to a lesser extent (Peter et al., 2008; Tasser and Tappeiner, 2002; Weber et al., 2018). We analyzed these relationships between GM and topography by comparing the GM classes based on the classwise distributions of elevation and slope (see Section 2.2.2; Table 1).

Third, we evaluated the GM classes using the georeferenced grassland use data for the canton of Berne in 2015 (see Section 2.2.3; Table 2). The conventional cantonal grassland use classes ("Meadow", "Pasture") are characterized by higher variability and use intensity in terms of M_{freq} and fertilizer inputs compared to the biodiversity promotion classes ("Meadow BPA", "Pasture BPA"; AGRIDEA, 2018; SFA, 2018). We assessed the representativeness of the GM classes according to the cantonal grassland classes by identifying the areal proportions of the GM classes within each cantonal grassland class.

Fourth, we evaluated the GM classes based on semi-quantitative GM information from the three subregions LU, ZH, and JU (see Section 2.2.4; Table 3). Use intensity decreased and the dominance of grazing increased in the order LU, ZH, JU. We assessed how well the GM classes match GM in the three subregions. Thus, we determined the areal proportion of each GM class within each subregion.

Fifth, we evaluated the GM classes by a comparison to established management related change patterns of SR, $N_{Landolt}$, $MT_{Brie.}$, and $GT_{Brie.}$ (see Section 2.2.5; Table 4). In this context, SR decreases with higher grassland use intensity (Allan et al., 2015; Gossner et al., 2016; Socher et al. 2013). Moreover, $N_{Landolt}$, $MT_{Brie.}$, and $GT_{Brie.}$ increases with higher use intensity (Blüthgen et al., 2012; Peter et al., 2008; Weber et al., 2018). We investigated the relationships between GM and grassland vegetation by comparing the GM classes based on the classwise distributions of SR, $N_{Landolt}$, MT_{Brie}, $GT_{Brie.}$.

Table 4
Summary statistics for the vegetation data (SR, $N_{Landolt}$, $MT_{Brie.}$, $GT_{Brie.}$: see Section 2.2.5; Min: Minimum; Q1: 25%-quartile; Q3: 75%-quartile; Max: Maximum; SD: Standard deviation).

	Min	Q1	Median	Mean	Q3	Max	SD
SR [-]	12	21	26	26	30	44	7
$N_{Landolt}$	3.1	3.5	3.7	3.6	3.8	4	0.2
$GT_{Brie.}$	4.5	5.3	5.7	5.7	6.1	6.8	0.5
$MT_{Brie.}$	5.6	6.8	7.1	7.0	7.3	7.7	0.4

Classwise outliers of the respective evaluation data, defined by a distance of two standard deviations from the mean, were removed for the analyses. Tukey's HSD tests were used to analyze the difference of classwise distributions with respect to BP and topography. Statistical calculations were performed using the R-package "base" and "stats", while the R-packages "raster" and "rgdal" were applied for geospatial processing (Hijmans et al., 2017,; Bivand et al., 2016; R Core Team, 2016).

3. Results

3.1. Grassland management classes and NDVI patterns

The NDVI profiles of the GM classes show statistical conformity with established change patterns for grassland (Fig. 3a, d; see Sections 2.2.1 and 2.3.2). The mean NDVI profile changes for all GM classes show bimodal temporal distributions, while use intensities are higher for meadows than for pastures with an increase across the classwise intensity graduation ("low", "moderate", "high"). The standard deviations (SDs) of the pasture classes increase in the order "$Pasture_{low}$" (SD = 0.046), $Pasture_{moderate}$ (SD = 0.049), $Pasture_{high}$ (SD = 0.50). The profiles of the meadow classes are consistently more variable, but SDs increase in the same order, $Meadow_{low}$ (SD = 0.056), $Meadow_{moderate}$ (SD = 0.062), "$Meadow_{high}$" (SD = 0.065). The median NDVI of the classwise profiles (M_{med}) varies in the same way as the variability increases, with M_{med} being 0.04 for $Pasture_{low}$, 0.056 for $Pasture_{moderate}$, 0.067 for $Pasture_{high}$, 0.078 for $Meadow_{low}$, 0.103 for $Meadow_{moderate}$, and 0.113 for $Meadow_{high}$. For all the GM classes, management was more frequent in May, July, and less pronounced in September (Fig. 3a; Appendix A-B). The classwise profiles of the absolute changes in NDVI for the randomly selected sites show similar but less distinct patterns compared with the mean NDVI profile changes (Fig. 3b–c; Appendix B-C). The median BP of the GM classes indicates higher use intensity for meadows than for pastures and an increase from low to high intensity grades. The median BP values are 0.13 to 0.253 and 0.366 for $Pasture_{low}$, $Pasture_{moderate}$, and $Pasture_{high}$, respectively, and 0.34, 0.501, and 0.619 for $Meadow_{low}$, $Meadow_{moderate}$, and $Meadow_{high}$ (Fig. 3d; Appendix C).

3.2. Grassland management classes and topography

The topography of the GM classes corresponds to established patterns of grassland use intensity (Fig. 4a; Table 1; see Sections 2.2.2 and 2.3.2). Slopes are lower for meadows than pastures, and decrease as use intensity increases. The median slopes are 12° for $Pasture_{low}$, 10° for $Pasture_{moderate}$, 9° for $Pasture_{high}$, 8° for $Meadow_{low}$, 7° for $Meadow_{moderate}$, and 6° for $Meadow_{high}$. Elevations decrease as the use intensity increases and are slightly lower for meadows than pastures (Fig. 4b). The median elevations are 748 m for $Pasture_{low}$, 720 m

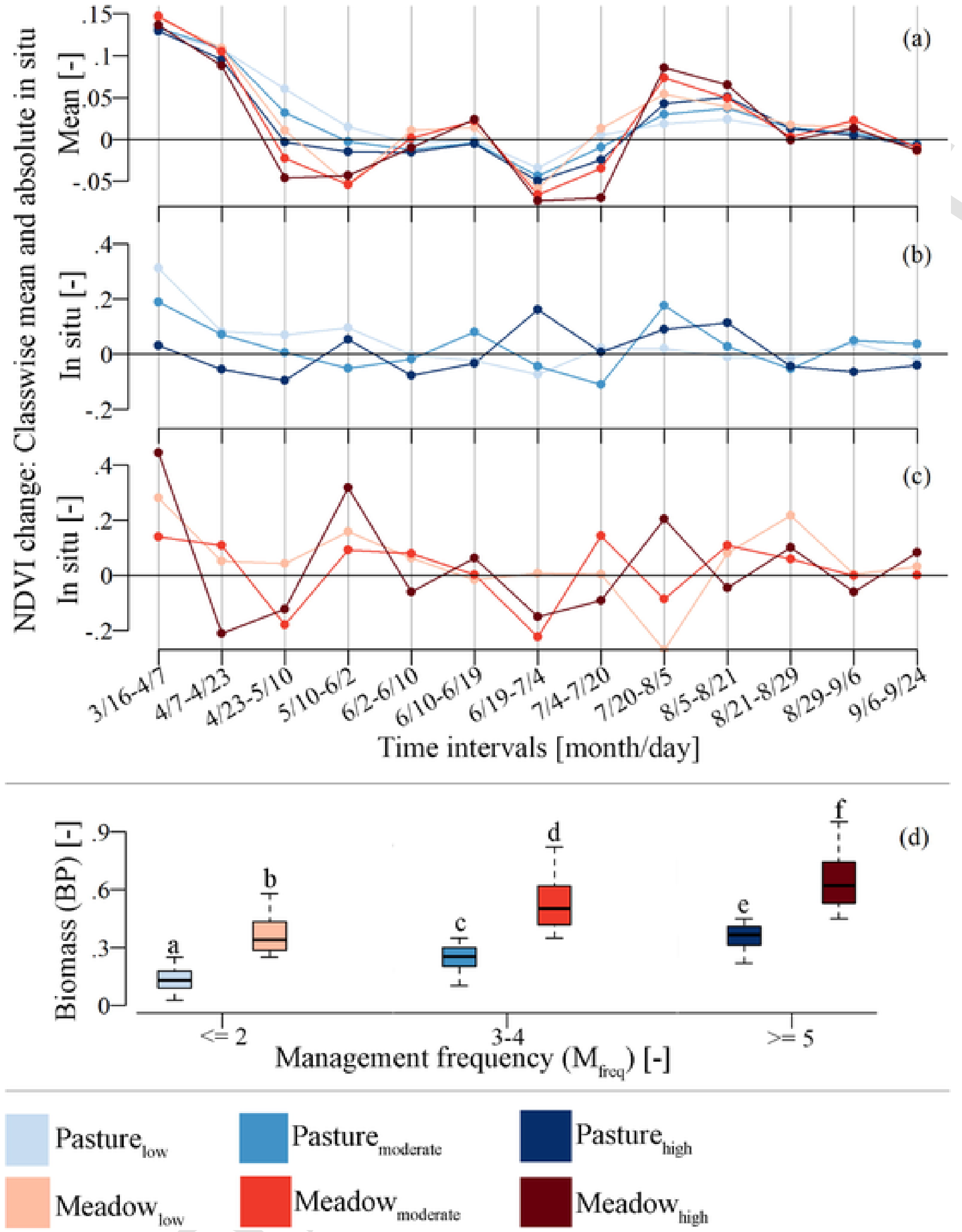

Fig. 3. The grassland management classes described by temporal profiles of mean NDVI changes (a), by temporal profiles of NDVI changes from randomly selected locations (in situ; b–c), and related to the underlying biomass productivity (BP) and management frequency (M_{freq}, d). Significant differences between the classwise distributions (Tukey HSD, $P < 0.05$) are indicated by different letters above the boxplots.

for $\text{Pasture}_{\text{moderate}}$, 667 m for $\text{Pasture}_{\text{high}}$, 712 m for $\text{Meadow}_{\text{low}}$, 687 m for $\text{Meadow}_{\text{moderate}}$, and 649 m for $\text{Meadow}_{\text{high}}$ (Appendix D).

3.3. Grassland management classes and cantonal grassland use

The GM classes spatially match the main patterns of the grassland use data for the canton of Berne (Fig. 5; Table 2; see Sections 2.2.3 and 2.3.2). For example, 85% and 79% of the cantonal meadow classes Meadow and Meadow BPA, respectively, are covered by the GM meadow classes ($\text{Meadow}_{\text{low}}$, $\text{Meadow}_{\text{moderate}}$, $\text{Meadow}_{\text{high}}$). The high intensity GM meadow class ($\text{Meadow}_{\text{high}}$) covers 11% less of the biodiversity promoting meadow class (Meadow BPA) than the conventional meadow class (Meadow). The cantonal pasture classes Pasture and Pasture BPA are covered by 93% and 100%, respectively, by the GM pasture classes ($\text{Pasture}_{\text{low}}$, $\text{Pasture}_{\text{moderate}}$, $\text{Pasture}_{\text{high}}$). The GM class $\text{Pasture}_{\text{low}}$ covers 10% more of the biodiversity promoting pasture class (Pasture BPA) than the conventional pasture class (Pasture; Appendix E).

3.4. Grassland management classes and subregional grassland use

The GM classes capture the main GM patterns of the subregions LU, ZH, and JU (Fig. 6; Table 3; see Sections 2.2.4 and 2.3.2). With an increase of mowing frequency and livestock density in the order JU, ZH, LU, the areal proportions of GM meadow classes increase, while the areal proportions of GM pasture classes show a contrary trend. For example, JU is dominated by low intensity grazing (livestock density index: 0.94 LSU*ha-1), which is reproduced by the GM pasture classes with an areal proportion of 73% and prevailing low to moderate intensities ($\text{Pasture}_{\text{low}}$: 13%, $\text{Pasture}_{\text{moderate}}$: 49%, $\text{Pasture}_{\text{high}}$: 11%).

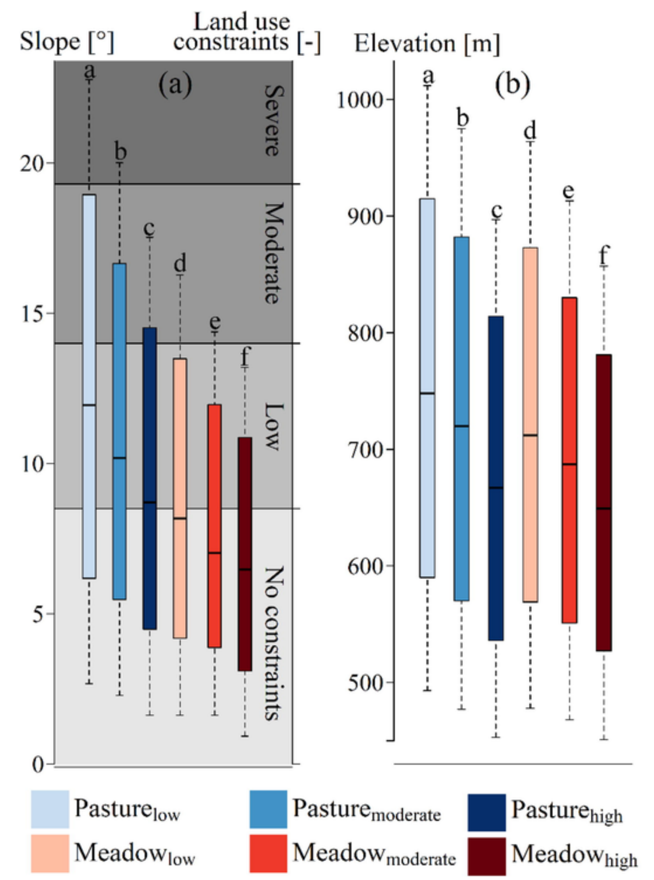

Fig. 4. Grassland management classes compared to slope as proxy for land use constraints (a), and to elevation as proxy for the length of the growth period (b). Significant differences between the classwise distributions (Tukey HSD, $P < 0.05$) are indicated by different letters above the boxplots.

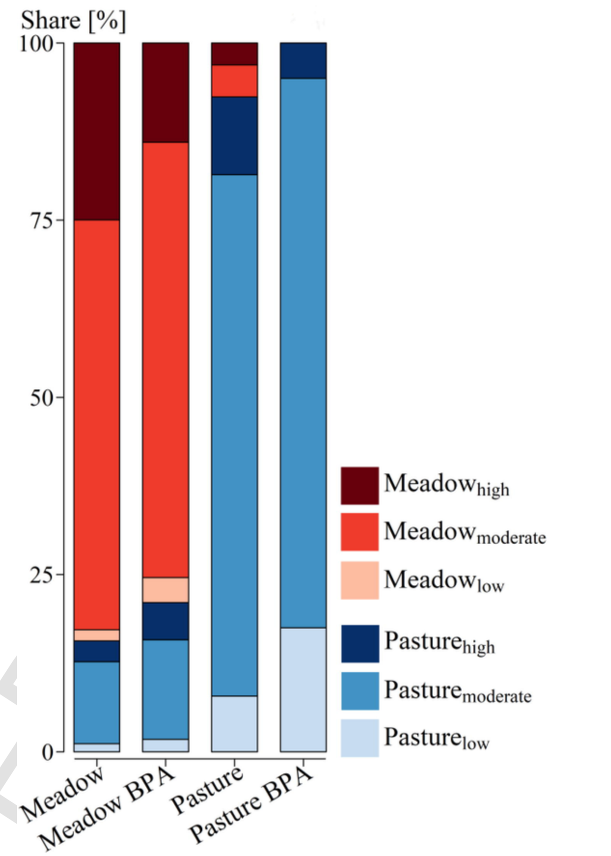

Fig. 5. The areal proportions of the grassland management classes within the cantonal land use classes of Berne (Meadow, Meadow BPA, Pasture, Pasture BPA; BPA: Biodiversity promotion area).

The mixture of mowing and grazing at different intensities in ZH (mowing frequency: 2–5; livestock density index: 1.36 LSU*ha-1) is reproduced by the GM classes with high areal proportions of moderate to high intensity GM pasture and meadow classes (Pasture$_{moderate}$: 31%, Pasture$_{high}$: 13%, Meadow$_{moderate}$: 29%, Meadow$_{high}$: 15%). The LU subregion is dominated by high intensity mowing (mowing frequency: >5; livestock density index: 1.87 LSU*ha-1), which is reproduced by GM meadow classes of moderate to high use intensity with an areal proportion of 74% (Meadow$_{moderate}$: 37%, Meadow$_{high}$: 37%; Appendix A).

3.5. Grassland management classes and vegetation patterns

Changes of plotdata-SR, -N$_{Landolt}$, -GT$_{Brie.}$, and -MT$_{Brie.}$ across the GM classes correspond to established patterns related to grassland use intensity (Fig. 7; Table 4; see Sections 2.2.5 and 2.3.2). SR is higher for pastures than meadows, and decreases as use intensity increases. The classwise median SR values are 33 for Pasture$_{low}$, 28 for Pasture$_{moderate}$, 26 for Pasture$_{high}$, 27 for Meadow$_{low}$, 23 for Meadow$_{moderate}$, and 21 for Meadow$_{high}$. N$_{Landolt}$ is lower for pastures than meadows, and increases with higher use intensity, confirming the well-known negative correlation with SR (Appendix F, G). The classwise increase of N$_{Landolt}$ is more pronounced for meadows. The median N$_{Landolt}$ values are 3.53 for Pasture$_{low}$, 3.53 for Pasture$_{moderate}$, 3.56 for Pasture$_{high}$, 3.61 for Meadow$_{low}$, 3.67 for Meadow$_{moderate}$, and 3.74 for Meadow$_{high}$. Similar trends are observed for GT$_{Brie.}$ and MT$_{Brie.}$. The classwise median GT$_{Brie.}$ values are 5.34 for Pasture$_{low}$, 5.7 for Pasture$_{moderate}$, and 5.86 for Pasture$_{high}$, while the median MT$_{Brie.}$ values range from 6.79 for Meadow$_{low}$, 7.14 for Meadow$_{moderate}$ to 7.15 for Meadow$_{high}$ (Appendix F, G).

4. Discussion

4.1. Mapping grassland management

Mapping GM from multi-temporal satellite imagery is often confined to a spatial representation of use intensity, disregarding the heterogeneity of GM practices (Green et al., 2016; Kolecka et al., 2018; Li et al., 2017). However, GM practices alternate spatially and often involve combinations of grazing and mowing at different intensities (Asam et al., 2015; Jeangros and Thomet, 2004). Integrating GM practices and use intensity is therefore highly relevant when monitoring spatial patterns of GM (Erb et al., 2013; Kuemmerle et al., 2013). In this study, we mapped the dominance of mowing and grazing, combined with associated use intensities exemplarily for Swiss grasslands in 2015. Pixelwise spectral time series were used to estimate M$_{freq}$ and BP in order to subsequently define GM according to six classes using a stepwise classification and clustering approach (Fig. 3; see Section 2.3.1). A similar method was previously applied for the Swiss case by Giménez et al. (2017), who mapped mowing frequencies and grazing intensities for an area of 67 km^2 based on RapidEye data. However, their approach was limited to spectral time series of only five time steps and a fragmentary coverage of the growth period. The pixel resolution of 5 m × 5 m allowed to capture small structured land use patterns, but the commercial nature and a relatively low spatial coverage of RapidEye data qualifies particularly for mapping small areas. Other studies used MODIS imagery (Moderate Resolution Imaging Spectroradiometer), which are available at a daily basis and a spatial resolution of 250 m × 250 m since 2002, and therefore

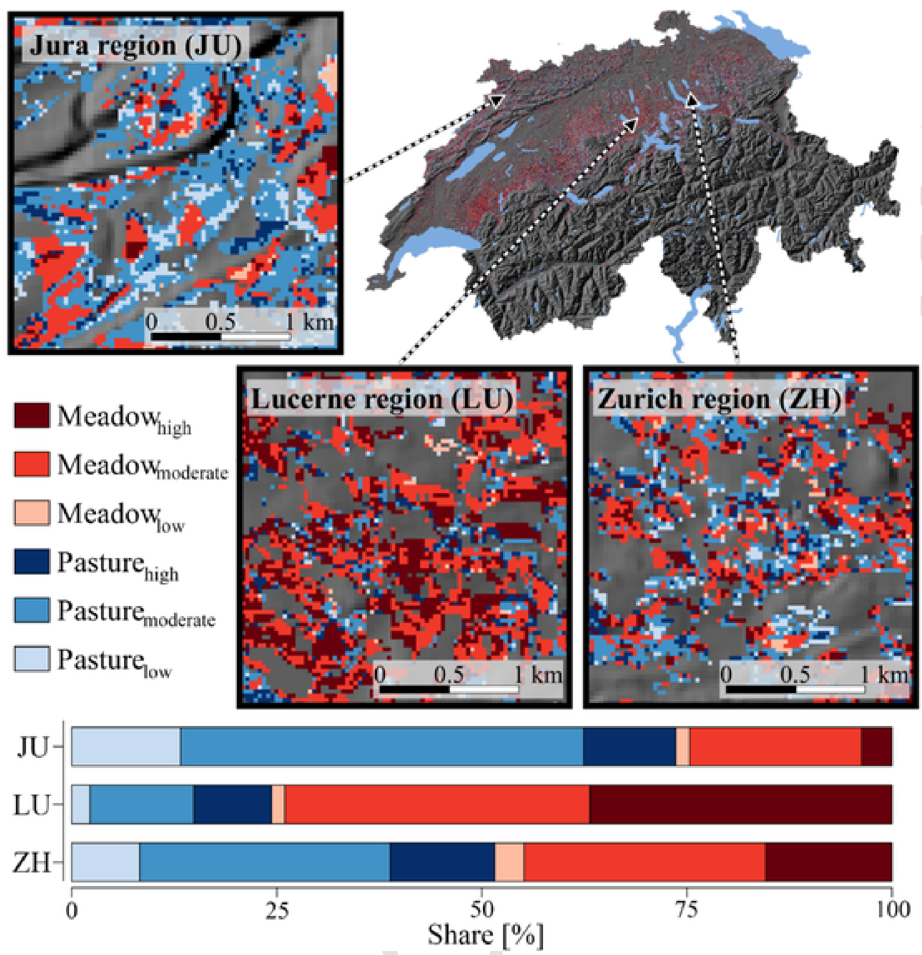

Fig. 6. Mapped grassland management classes and their areal proportions within three subregions of characteristic grassland management in Switzerland (JU: Jura, LU: Lucerne, ZH: Zurich).

mainly qualify to map large areas with homogenous spatio-temporal landscape structures (Estel et al., 2018; Green et al., 2016; Li et al., 2017). Monitoring exercises targeting current and future GM benefit from the use of Sentinel imagery, which are characterized by a revisit of 3–10 days and a spatial resolution of 10 m × 10 m, available since 2017 (Claverie et al., 2018; Griffiths et al., 2019; Kolecka et al., 2018). We used spectral data from the Landsat archive, available since 1984 and allowing to annually cover large areas with dense time series for timely capturing land use activities at national scale and for most of the growth period. Our Landsat time series for 2015 covers the growth period in 14 time steps and the grassland area by 89% at a spatial resolution of 30 m × 30 m (Figs. 1, 2).

GM classes were determined by identifying management related patterns in the temporal profiles of spectral time series (Ali et al., 2016). The profiles describe dynamics of biophysical vegetation properties based on NDVI as indicator for plant biomass (Dusseux et al., 2014b; Psomas et al., 2011). The strength of the NDVI-biomass relationship varies spatially, determined by local site characteristics with respect to plant species composition, vegetation growth stage, topography, soil exposure, and dense biomass (Garroutte et al., 2016; Metzger et al., 2016; Porter et al., 2014). However, NDVI has been approved to be a stable and robust biomass proxy in various landscapes (Ali et al., 2016; Nestola et al., 2016; Zhang et al., 2003). In the present study, we used the NDVI because it is resistant to spectral noise, caused by topography and cloud shadows, particularly for rugged terrain (Huete et al., 2002). Moreover, remote sensing based NDVI profiles have been approved to be a reliable data source to describe grassland management in the Swiss context. Kolecka et al. (2018) successfully mapped mowing frequencies in the northern Swiss canton Aargau (1403 km^2) based on NDVI profiles from Sentinel imagery. Weber et al. (2018) showed the adequacy of Landsat NDVI profiles to discriminate grassland management practice and use intensity at 3000 sites distributed across Switzerland and covering ~240 km^2.

4.2. Validity of the grassland management classes

The GM classes were evaluated with respect to typical NDVI profiles for GM, topographical site conditions related to GM, cantonal grassland use data, and semi-quantitative grassland use data from three subregions. Moreover, the GM classes were evaluated using established management related change patterns of species richness (SR), and vegetation based indicator values for nutrient supply ($N_{Landolt}$) and management tolerance ($MT_{Brie.}$, $GT_{Brie.}$; see Section 2.3.2).

Temporal NDVI profiles of the proposed GM classes are statistically distinct, while showing higher variabilities, BPs, and M_{freq}, as well as enhanced bimodal distributions for meadows than for pastures and from low to high use intensity. Thus, the GM classes match typical management related NDVI patterns for grassland systems (Fig. 3; Appendix B-C; Dusseux et al., 2014a, b; Fang et al., 2015; Taugourdeau et al., 2013; Weber et al., 2018).

Elevations and slopes of the GM classes are lower for meadows than pastures and decrease as the use intensity increases. These patterns indicate the validity of the GM classes, because with increasing eleva-

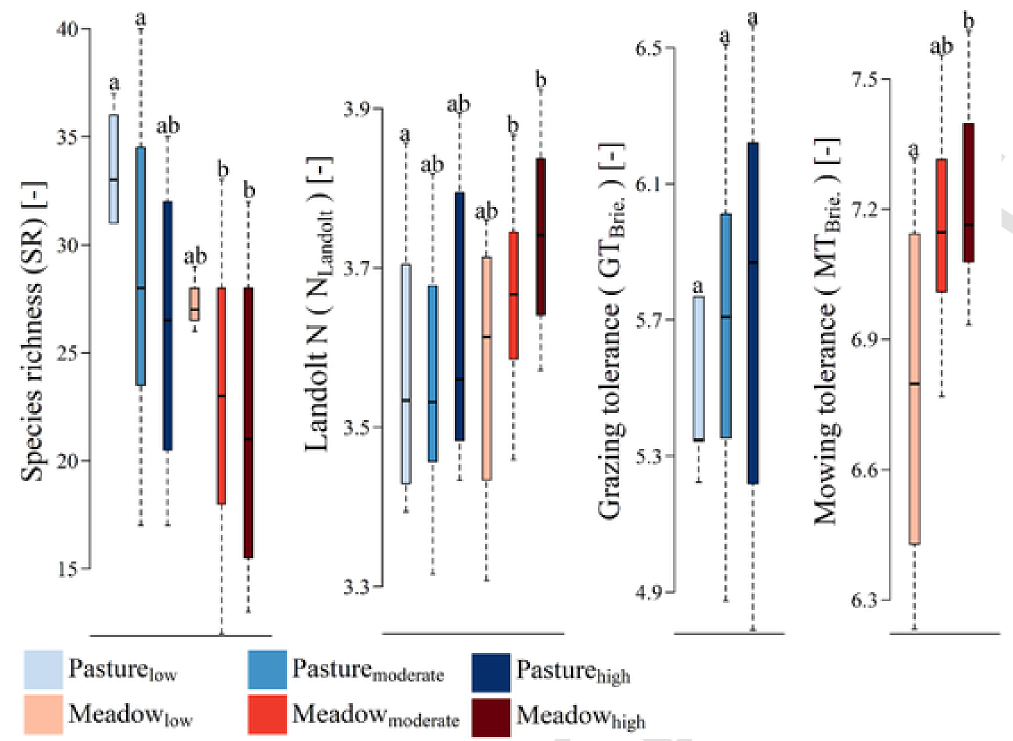

Fig. 7. Grassland management classes compared to species richness (SR), to Landolt N ($N_{Landolt}$), to grazing tolerance ($GT_{Brie.}$), and to mowing tolerance ($MT_{Brie.}$). Significant differences between the classwise distributions (Tukey HSD, $P < 0.05$) are indicated by different letters above the boxplots.

tion BP is incrementally limited due to a lower mean temperature and shorter growth period (Fig. 4b; Schermer et al., 2016; Weber et al., 2018; Zeeman et al., 2010). In addition, increasing slopes hamper the use of machinery for GM, which is associated with decreased use intensity (Fig. 4a; Appendix D; Lamarque et al., 2011; Peter et al., 2008; Tasser and Tappeiner, 2002). The large overlapping ranges in the elevation and slopes of the GM classes for the entire Swiss grassland <1400 m (a.s.l.) could be attributed to typical spatial variability in BP, caused by numerous interrelated factors, such as topography, climate, soil quality, and species composition (Porqueddu et al., 2016).

The GM classes are consistent in terms of spatial and contextual detail with georeferenced data on grassland use for the canton of Berne. The conformity is very high for pastures, but lower for meadows, which could be explained by grazing events that are possible according to the class definition of the cantonal land use data (Fig. 5; Appendix E; AGRIDEA, 2018, SFA, 2018). This discrepancy in class definitions also explains the relatively small deviations between the GM classes and the cantonal data comparing conventional and BPA meadows and pastures, respectively.

Regional differences in GM of the subregions in the cantons Lucerne (LU), Zurich (ZH), and Jura (JU) are realistically reflected in the GM classes. For instance, LU with a long growth period, high livestock densities, and mowing frequencies is largely characterized by moderate to high intensity GM meadow classes. In contrast, ZH and JU with shorter growth periods, lower livestock densities, but predominantly managed by grazing are characterized by larger proportions of low to moderate GM pasture classes (Fig. 6; Appendix A; Chételat et al., 2013; Giménez et al., 2017; Masé, 2005).

Our results reveal trends of decreasing SR, as well as increasing $N_{Landolt}$, $MT_{Brie.}$, and $GT_{Brie.}$ along the increase of use intensity. These trends reproduce established change patterns of species diversity, nutrient availability, and management tolerance on agricultural grasslands (Blüthgen et al., 2012; Peter et al., 2008; Weber et al., 2018). Some of the difference between pasture and meadow GM classes may also stem from the geographical distribution of the two classes, e.g. more pastures at steeper slopes and higher elevations. The large overlapping ranges in species based variables (SR, $N_{Landolt}$, $MT_{Brie.}$, $GT_{Brie.}$) of the GM classes could be associated to relatively low SR ranges for pastures of the used data, as well as to the limited and imbalanced number observations n across the GM classes (Fig. 7; Appendix F-G; $SR_{Pastures}$: 17–44; $SR_{Meadows}$: 12–39; $n_{Pastures}$: 6–29; $n_{Meadows}$: 4–38). Previous studies found SR ranges of 24–64 for pastures and 10–36 for meadows with different grazing and mowing frequencies (Kleijn and Müller-Schärer, 2006; Liebisch et al., 2013, Pauler et al., 2019). However, observed differences between meadows and pastures, and vegetation trends along the GM intensity gradient, approve the GM classification to be robust. The generally large variability of SR observed in the GM classes is likely an effect of additional factors such as nutrient management or regional differences in species abundance among others.

5. Conclusion

The developed spatial monitoring tool for detecting grassland management systems discriminates mowing and grazing practices, as well as associated use intensities for Swiss grasslands. The tool is based on high resolution spectral time series derived from freely available satellite images with adequate spatial resolution. This data source allows small structured agroecosystems and frequent management activities to be captured at the national scale and on an annual basis for future and retrospective studies. We applied the grassland monitoring tool exemplarily for the growth period of the year 2015. The plausibility of the tool was approved by an evaluation scheme that includes regional land use data, as well as established management related patterns of NDVI phenology, topography and vegetation. The land use information provided by the grassland monitoring tool may help to establish a balance between agricultural production and the maintenance of ecosystem functioning at the landscape scale.

Uncited reference

.

CRediT authorship contribution statement

Felix Stumpf: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Manuel K. Schneider:** Methodology, Software, Validation, Formal analysis, Writing - review & editing, Visualization. **Armin Keller:** Conceptualization, Validation, Formal analysis, Resources, Data curation, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Andreas Mayr:** Formal analysis, Writing - review & editing. **Tobias Rentschler:** Software. **Reto G. Meuli:** Validation, Resources, Writing - review & editing, Supervision, Project administration. **Michael Schaepman:** Conceptualization, Validation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Frank Liebisch:** Methodology, Validation, Formal analysis, Writing - review & editing, Visualization.

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

This study contributes to the development of a spatially distributed Land management Model for the Swiss Plateau that links agricultural management to soil services and policies (Project Number: 406840-161896). The project is funded by the Swiss National Science Foundation within the framework of the National Research Program "Sustainable Use of Soil as a Resource" (NRP 68; www.nrp68.ch). The contribution of Michael Schaepman is supported by the University of Zurich Research Priority Program on Global Change and Biodiversity (URPP GCB).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106201.

References

AGIS, 2017. Agricultural Information System AGIS (Swiss Federal Office for Agriculture FOAG). https://www.blw.admin.ch/blw/de/home/politik/datenmanagement/agate/agis.html. (Accessed October 2018).
AGRIDEA, 2018. Centre for Agricultural Advisory and Environment. http://www.agridea.ch/en/publications/publication/environment-nature-and-landscape/legal-and-administrative-aspects/promotion-de-la-biodiversite-dans-lexploitation-agricole/. (Accessed July 2018).
Ali, I., Cawkwell, F., Dwyer, E., Barrett, B., Green, S., 2016. Satellite remote sensing of grasslands: from observation to management. J. Plant Ecol. 9, 649–671.
Allan, E., Bossdorf, O., Dormann, C.F., Prati, D., Gossner, M.M., Tscharntke, T., Blüthgen, N., Bellach, M., Birkhofer, K., Boch, S., 2014. Interannual variation in land-use intensity enhances grassland multidiversity. Proc. Natl. Acad. Sci. 111, 308–313.
Allan, E., Manning, P., Alt, F., Binkenstein, J., Blaser, S., Blüthgen, N., Böhm, S., Grassein, F., Hölzel, N., Klaus, V.H., 2015. Land use intensification alters ecosystem multifunctionality via loss of biodiversity and changes to functional composition. Ecol. Lett. 18, 834–843.
Allen, V.G., Batello, C., Berretta, E., Hodgson, J., Kothmann, M., Li, X., McIvor, J., Milne, J., Morris, C., Peeters, A., 2011. An international terminology for grazing lands and grazing animals. Grass Forage Sci. 66, 2–28.
Asam, S., Klein, D., Dech, S., 2015. Estimation of grassland use intensities based on high spatial resolution LAI time series. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 40, pp. 285–291.
Askari, M.S., Holden, N.M., 2014. Indices for quantitative evaluation of soil quality under grassland management. Geoderma 230, 131–142.
Bartelheimer, M., Poschlod, P., 2016. Functional characterizations of Ellenberg indicator values–a review on ecophysiological determinants. Funct. Ecol. 30, 506–516.
BDM, 2014: Swiss Biodiversity Monitoring – Methods and Indicators. https://www.bafu.admin.ch/bafu/en/home/topics/biodiversity/publications-studies/publications/biodiversity-monitoring.html. (Accessed October 2019).
BDM, 2017. Biodiversity Monitoring Switzerland. http://www.biodiversitymonitoring.ch/fileadmin/user_upload/documents/daten/anleitungen/1440_Anleitung_Z9-Pflanzen_v13.pdf. (Accessed July 2018).
Bivand, R., Keitt, T., Rowlingson, B., 2016. rgdal: Bindings for the Geospatial Data Abstraction Library. R package version 1.1-9, 'rgdal' package.
Blüthgen, N., Dormann, C.F., Prati, D., Klaus, V.H., Kleinebecker, T., Hölzel, N., Alt, F., Boch, S., Gockel, S., Hemp, A., 2012. A quantitative index of land-use intensity in grasslands: integrating mowing, grazing and fertilization. Basic Appl. Ecol. 13, 207–220.
Briemle, G., Nitsche, S., Nitsche, L., 2002. Nutzungswertzahlen für Gefäßpflanzen des Grünlandes. Bundesamt für Naturschutz, Schriftenreihe für Vegetationskunde 38, 203–225.
Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., 2012. Biodiversity loss and its impact on humanity. Nature 486, 59–67.
Chételat, J., Kalbermatten, M., Lannas, K.S., Spiegelberger, T., Wettstein, J.-B., Gillet, F., Peringer, A., Buttler, A., 2013. A contextual analysis of land-use and vegetation changes in two wooded pastures in the Swiss Jura Mountains. Ecol. Soc. 18, 39.
Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J.-C., Skakun, S.V., Justice, C., 2018. The Harmonized Landsat and Sentinel-2 surface reflectance data set. Remote Sens. Environ. 219, 145–161.
Diekmann, M., 2003. Species indicator values as an important tool in applied plant ecology–a review. Basic Appl. Ecol. 4, 493–506.
Duprè, C., Stevens, C.J., Ranke, T., Bleeker, A., Peppler-Lisbach, C., Gowing, D.J., Dise, N.B., Dorland, E., Bobbink, R., Diekmann, M., 2010. Changes in species richness and composition in European acidic grasslands over the past 70 years: the contribution of cumulative atmospheric nitrogen deposition. Glob. Change Biol. 16, 344–357.
Dusseux, P., Vertès, F., Corpetti, T., Corgne, S., Hubert-Moy, L., 2014. Agricultural practices in grasslands detected by spatial remote sensing. Environ. Monit. Assess. 186, 8249–8265.
Dusseux, P., Corpetti, T., Hubert-Moy, L., Corgne, S.J.R.S., 2014. Combined use of multi-temporal optical and radar satellite images for grassland monitoring. Remote Sensing 6, 6163–6182.
EC, 2018. The common agricultural policy. https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy_en. (Accessed October 2018).
Ellenberg, H., 1974. Indicator values of vascular plants in central Europe. In: Scripta Geobotanica. Goltze Publishing, Göttingen, Germany.
Erb, K.-H., Haberl, H., Jepsen, M.R., Kuemmerle, T., Lindner, M., Müller, D., Verburg, P.H., Reenberg, A., 2013. A conceptual framework for analysing and measuring land-use intensity. Curr. Opin. Environ. Sustain. 5, 464–470.
Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., Hostert, P., 2015. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. Remote Sens. Environ. 163, 312–325.
Estel, S., Mader, S., Levers, C., Verburg, P.H., Baumann, M., 2018. Combining satellite data and agricultural statistics to map grassland management intensity in Europe. Environ. Res. Lett. 13, 074020.
Fang, J., Bai, Y., Wu, J., 2015. Towards a better understanding of landscape patterns and ecosystem processes of the Mongolian Plateau. Landsacpe Ecol. 30, 1573–1578.
Flynn, E.S., Dougherty, C.T., Wendroth, O.J.A.J., 2008. Assessment of pasture biomass with the normalized difference vegetation index from active ground-based sensors. Agron. J. 100, 114–121.
FOAG, 2018. Swiss agricultural policy. https://www.cbd.int/financial/pes/swiss-pesagriculturalpolicy.pdf. (Accessed October 2018).
Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., 2011. Solutions for a cultivated planet. Nature 478, 337–342.
Gao, T., Xu, B., Yang, X., Jin, Y., Ma, H., Li, J., Yu, H., 2013. Using MODIS time series data to estimate aboveground biomass and its spatio-temporal variation in Inner Mongolia's grassland between 2001 and 2011. Int. J. Remote Sens. 34, 7796–7810.
Garroutte, E.L., Hansen, A.J., Lawrence, R.L., 2016. Using NDVI and EVI to map spatiotemporal variation in the biomass and quality of forage for migratory elk in the Greater Yellowstone ecosystem. Remote Sens. 8, 404.
Gärtner, D., Keller, A., Schulin, R., 2013. A simple regional downscaling approach for spatially distributing land use types for agricultural land. Agric. Syst. 120, 10–19.
Giménez, M.G., de Jong, R., Della Peruta, R., Keller, A., Schaepman, M.E., 2017. Determination of grassland use intensity based on multi-temporal remote sensing data and ecological indicators. Remote Sens. Environ. 198, 126–139.
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27.
Gossner, M.M., Lewinsohn, T.M., Kahl, T., Grassein, F., Boch, S., Prati, D., Birkhofer, K., Renner, S.C., Sikorski, J., Wubet, T., 2016. Land-use intensification causes multitrophic homogenization of grassland communities. Nature 540, 266–269.
Green, S., Cawkwell, F., Dwyer, E., 2016. Cattle stocking rates estimated in temperate intensive grasslands with a spring growth model derived from MODIS NDVI time-series. International Journal of Applied Earth Observation and Geoinformation 52, 166–174.
Griffiths, P., Nendel, C., Pickert, J., Hostert, P., 2019. Towards national-scale characterization of grassland use intensity from integrated Sentinel-2 and landsat time series. Remote Sens. Environ. 238, 111124.
Habel, J.C., Dengler, J., Janišová, M., Török, P., Wellstein, C., Wiezik, M., 2013. European grassland ecosystems: threatened hotspots of biodiversity. Biodivers. Conserv. 22, 2131–2138.
Hartigan, J.A., Wong, M.A., 1979. Algorithm AS 136: A k-means clustering algorithm. J. R. Stat. Soc. Ser. C (Appl. Stat.) 28, 100–108.
Henle, K., Alard, D., Clitherow, J., Cobb, P., Firbank, L., Kull, T., McCracken, D., Moritz, R.F., Niemelä, J., Rebane, M., 2008. Identifying and managing the conflicts be-

tween agriculture and biodiversity conservation in Europe–A review. Agric. Ecosyst. Environ. 124, 60–71.
Hijmans, R.J., van Etten, J., Cheng, J., Mattiuzzi, M., Sumner, M., Greenberg, J.A., Lamigueiro, O.P., Bevan, A., Racine, E.B., Shortridge, A., 2017. Package 'raster'. R Foundation for Statistical Computing.
Horn, B.K., 1981. Hill shading and the reflectance map. Proc. IEEE 69, 14–47.
Hudewenz, A., Klein, A.-M., Scherber, C., Stanke, L., Tscharntke, T., Vogel, A., Weigelt, A., Weisser, W.W., Ebeling, A., 2012. Herbivore and pollinator responses to grassland management intensity along experimental changes in plant species richness. Biol. Conserv. 150, 42–52.
Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83, 195–213.
Huyghe, C., Vliegher, A.D., Goliński, P., 2014. European grasslands overview: temperate region. EGF at 50: The future of European grasslands. In: Proceedings of the 25th General Meeting of the European Grassland Federation, Aberystwyth, Wales, 7–11 September 2014. IBERS, Aberystwyth University, pp. 29–40.
Hyndman R.J., Fan, Y., 1996. Sample quantiles in statistical packages. The American Statistician 50. pp. 361–365.
Isselstein, J., Kayser, M., 2014. Functions of grassland and their potential in delivering ecosystem services. Future Eur. Grasslands 199–214.
Jeangros, B., Thomet, P., 2004. Multi-functionality of grassland systems in Switzerland. Grassland Sci. Eur. 9, 11–23.
Jiang, Y., Tao, J., Huang, Y., Zhu, J., Tian, L., Zhang, Y., 2014. The spatial pattern of grassland aboveground biomass on Xizang Plateau and its climatic controls. J. Plant Ecol. 8, 30–40.
Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—Temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910.
Kennedy, R.E., Andréfouët, S., Cohen, W.B., Gómez, C., Griffiths, P., Hais, M., Healey, S.P., Helmer, E.H., Hostert, P., Lyons, M.B., 2014. Bringing an ecological view of change to Landsat-based remote sensing. Front. Ecol. Environ. 12, 339–346.
Kizeková, M., Hopkins, A., Kanianska, R., Makovníková, J., Pollák, Š., Pálka, B., 2018. Changes in the area of permanent grassland and its implications for the provision of bioenergy: Slovakia as a case study. Grass Forage Sci. 73, 218–232.
Klaus, V.H., Kleinebecker, T., Boch, S., Müller, J., Socher, S.A., Prati, D., Fischer, M., Hölzel, N., 2012. NIRS meets Ellenberg's indicator values: Prediction of moisture and nitrogen values of agricultural grassland vegetation by means of near-infrared spectral characteristics. Ecol. Ind. 14, 82–86.
Kleijn, D., Baquero, R., Clough, Y., Diaz, M., De Esteban, J., Fernández, F., Gabriel, D., Herzog, F., Holzschuh, A., Jöhl, R., 2006. Mixed biodiversity benefits of agri-environment schemes in five European countries. Ecol. Lett. 9, 243–254.
Kleijn, D., Müller-Schärer, H., 2006. The relation between unpalatable species, nutrients and plant species richness in Swiss montane pastures. Biodivers. Conserv. 15, 3971–3982.
Kleijn, D., Sutherland, W.J., 2003. How effective are European agri-environment schemes in conserving and promoting biodiversity? J. Appl. Ecol. 40, 947–969.
Kleijn, D., Rundlöf, M., Scheper, J., Smith, H.G., Tscharntke, T., 2011. Does conservation on farmland contribute to halting the biodiversity decline? Trends Ecol. Evol. 26, 474–481.
Knop, E., Kleijn, D., Herzog, F., Schmid, B., 2006. Effectiveness of the Swiss agri-environment scheme in promoting biodiversity. J. Appl. Ecol. 43, 120–127.
Kolecka, N., Ginzler, C., Pazur, R., Price, B., Verburg, P., 2018. Regional scale mapping of grassland mowing frequency with sentinel-2 time series. Remote Sens. 10, 1221.
Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., 2013. Challenges and opportunities in mapping land use intensity globally. Curr. Opin. Environ. Sustain. 5, 484–493.
Lamarque, P., Tappeiner, U., Turner, C., Steinbacher, M., Bardgett, R.D., Szukics, U., Schermer, M., Lavorel, S.J.R., 2011. Stakeholder perceptions of grassland ecosystem services in relation to knowledge on soil fertility and biodiversity. Regional Environ. Change 11, 791–804.
LANAT, 2018. Cantonal Office for Agriculture and Environment, Berne. http://www.vol.be.ch/vol/de/index/landwirtschaft/landwirtschaft.html. (Accessed July 2018).
Landolt, E., Bäumler, B., Erhardt, A., Hegg, O., Klötzli, F., Lämmler, W., Nobis, M., Rudmann-Maurere, K., Schweingruber, F.H., Theurillat, J.P., Urmi, E., Vust, M., Wohlgemuth, T., 2010. Flora Indicativa – Ecological Indicator Values and Biological Attributes of the Flora of Switzerland and the Alps. second ed. Haupt Publishing, Berne, Switzerland.
Leifeld, J., Fuhrer, J., 2005. Greenhouse gas emissions from Swiss agriculture since 1990: implications for environmental policies to mitigate global warming. Environ. Sci. Policy 8, 410–417.
Leifeld, J., Bassin, S., Fuhrer, J., 2005. Carbon stocks in Swiss agricultural soils predicted by land-use, soil characteristics, and altitude. Agric. Ecosyst. Environ. 105, 255–266.
Li, F., Bai, Y., Wan, H., Zheng, J., Luo, J., Zhao, D., Liu, P., 2017. Quantifying grazing intensity in China using high temporal resolution MODIS data. IEEE J. Selected Top. Appl. Earth Observ. Remote Sens. 10, 515–523.
Liebisch, F., Bünemann, E.K., Huguenin-Eilie, O., Jeangros, B., Frossard, E., Oberson, A., 2013. Plant phosphorus nutrition indicators evaluated in agricultural grasslands managed at different intensities. Eur. J. Agron. 44, 67–77.
Liebisch, F., 2011. Plant and soil indicators to assess the phosphorus nutrition status of agricultural grasslands. ETH Zurich.
Liu, S., Cheng, F., Dong, S., Zhao, H., Hou, X., Wu, X., 2017. Spatiotemporal dynamics of grassland aboveground biomass on the Qinghai-Tibet Plateau based on validated MODIS NDVI. Sci. Rep. 7, 4182.
Masé, G., 2005. The management of dry grassland in Switzerland. A Swiss federal program and its local practical application. Biotechnologie Agronomie Société et Environnement 9, 133–138.
MeteoSwiss, 2018b. Documentation of MeteoSwiss grid-data products. Daily precipitation (final analysis): RhiresD. https://www.meteoswiss.admin.ch/content/dam/meteoswiss/de/service-und-publikationen/produkt/raeumliche-daten-niederschlag/doc/ProdDoc_RhiresD.pdf. (Accessed July 2018).
MeteoSwiss, 2018a. Documentation of MeteoSwiss grid-data products. Daily mean, minimum and maximum temperature: TabsD, TminD, TmaxD. https://www.meteoswiss.admin.ch/content/dam/meteoswiss/de/service-und-publikationen/produkt/raeumliche-daten-temperatur/doc/ProdDoc_TabsD.pdf. (Accessed July 2018).
Metzger, C.M.H., Heinichen, J., Eickenscheidt, T., Drosler, M., 2016. Impact of land-use intensity on the relationship between vegetation indices, photosynthesis and biomass of intensively and extensively managed grassland fens. Grass Forage Sci. 72, 50–63.
Moog, D., Poschlod, P., Kahmen, S., Schreiber, K.F., 2002. Comparison of species composition between different grassland management treatments after 25 years. Appl. Veg. Sci. 5, 99–106.
Mottet, A., Ladet, S., Coqué, N., Gibon, A., 2006. Agricultural land-use change and its drivers in mountain landscapes: A case study in the Pyrenees. Agric. Ecosyst. Environ. 114, 296–310.
Nagendra, H., Lucas, R., Honrado, J.P., Jongman, R.H., Tarantino, C., Adamo, M., Mairota, P., 2013. Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. Ecol. Ind. 33, 45–59.
Nestola, E., Calfapietra, C., Emmerton, C.A., Wong, C., Thayer, D.R., Gamon, J.A., 2016. Monitoring grassland seasonal carbon dynamics, by integrating MODIS NDVI, proximal optical sampling, and eddy covariance measurements. Remote Sens. 8, 260.
O`Mara, F.P., 2012. The role of grasslands in food security and climate change. Ann. Bot. 110, 1263–1270.
Oenema, O., de Klein, C., Alfaro, M., 2014. Intensification of grassland and forage use: driving forces and constraints. Crop Pasture Sci. 65, 524–537.
Orr, R., Murray, P., Eyles, C., Blackwell, M., Cardenas, L., Collins, A., Dungait, J., Goulding, K., Griffith, B., Gurr, S., 2016. The North Wyke Farm Platform: effect of temperate grassland farming systems on soil moisture contents, runoff and associated water quality dynamics. Eur. J. Soil Sci. 67, 374–385.
Pauler, C.M., Isselstein, J., Braunbeck, T., Schneider, M.K., 2019. Influence of highland and production-oriented cattle breeds on pasture vegetation: A pairwise assessment across broad environmental gradients. Agric. Ecosyst. Environ. 284, 106585.
Pe'er, G., Dicks, L., Visconti, P., Arlettaz, R., Báldi, A., Benton, T., Collins, S., Dieterich, M., Gregory, R., Hartig, F., 2014. EU agricultural reform fails on biodiversity. Science 344, 1090–1092.
Peeters, A., Beaufoy, G., Canals, R., De Vliegher, A., Huyghe, C., Isselstein, J., Jones, J., Kessler, W., Kirilovsky, D., Van Den Pol-Van Dasselaar, A., 2014. Grassland term definitions and classifications adapted to the diversity of European grassland-based systems. In: 25th EGF General Meeting on "EGF at 50: The Future of European Grasslands, pp. 743–750.
Peter, M., Edwards, P.J., Jeanneret, P., Kampmann, D., Lüscher, A., 2008. Changes over three decades in the floristic composition of fertile permanent grasslands in the Swiss Alps. Agric. Ecosyst. Environ. 125, 204–212.
Porqueddu, C., Ates, S., Louhaichi, M., Kyriazopoulos, A., Moreno, G., del Pozo, A., Ovalle, C., Ewing, M., Nichols, P., 2016. Grasslands in 'Old World'and 'New World'Mediterranean-climate zones: past trends, current status and future research priorities. Grass Forage Sci. 71, 1–35.
Porter, T.F., Chen, C., Long, J.A., Lawrence, R.L., Sowell, B.F., 2014. Estimating biomass on CRP pastureland: A comparison of remote sensing techniques. Biomass Bioenergy 66, 268–274.
Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. London B: Biol. Sci. 365, 2959–2971.
Price, B., Kienast, F., Seidl, I., Ginzler, C., Verburg, P.H., Bolliger, J., 2015. Future landscapes of Switzerland: Risk areas for urbanisation and land abandonment. Appl. Geogr. 57, 32–41.
PRIF, 2017. Principles of fertilization of agricultural crops in Switzerland (PRIF 2017), Agroscope, Switzerland. https://www.agroscope.admin.ch/agroscope/en/home/topics/plant-production/field-crops/Pflanzenernaehrung/grud.html. (Accessed August 2018).
Psomas, A., Kneubühler, M., Huber, S., Itten, K., Zimmermann, N., 2011. Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats. Int. J. Remote Sens. 32, 9007–9031.
Pywell, R.F., Heard, M.S., Bradbury, R.B., Hinsley, S., Nowakowski, M., Walker, K.J., Bullock, J.M., 2012. Wildlife-friendly farming benefits rare birds, bees and plants. Biol. Lett. 8, 772–775.
R Core Team, 2016. R: A language and environment for statistical computing. pp. http://www.R-project.org/. (Accessed: March 2016).
Rodríguez, J.P., Beard, T.D., Jr, Bennett, E.M., Cumming, G.S., Cork, S.J., Agard, J., Dobson, A.P., Peterson, G.D., 2006. Trade-offs across space, time, and ecosystem services. Ecol. Soc. 11, 1–28.
Rose, L., Coners, H., Leuschner, C., 2012. Effects of fertilization and cutting frequency on the water balance of a temperate grassland. Ecohydrology 5, 64–72.
Rose, L., Leuschner, C., 2012. The diversity–productivity relationship in a permanent temperate grassland: negative diversity effect, dominant influence of management regime. Plant Ecol. Divers. 5, 265–274.
Rouse, J.W., Jr, Haas, R., Schell, J., Deering, D., 1974. Monitoring Vegetation Systems in the Great Plains with ERTS. University of Texas. Paper A20.
Sakowska, K., Juszczak, R., Gianelle, D., 2016. Remote sensing of grassland biophysical parameters in the context of the Sentinel-2 satellite mission. J. Sensors 2016, 4612809.
Schermer, M., Darnhofer, I., Daugstad, K., Gabillet, M., Lavorel, S., Steinbacher, M., 2016. Institutional impacts on the resilience of mountain grasslands: an analysis based on three European case studies. Land Use Policy 52, 382–391.
Schmidt, G., Jenkerson, C., Masek, J., Vermote, E., Gao, F., 2013. Landsat ecosystem disturbance adaptive processing system (LEDAPS) algorithm description. US Geological Survey.
Schweiger, A.K., Risch, A.C., Damm, A., Kneubühler, M., Haller, R., Schaepman, M.E., Schütz, M., 2015. Using imaging spectroscopy to predict above-ground plant biomass in alpine grasslands grazed by large ungulates. J. Veg. Sci. 26, 175–190.

SFA, 2018. Swiss Federal Administration, administrative order for agricultural terminology (910.91). https://www.admin.ch/opc/de/classified-compilation/19983381/201801010000/910.91.pdf. (Accessed July 2018).
SFSO, 2018. Swiss Federal Statistical Office: land use in Switzerland. Results of the Swiss land use statistics. https://www.bfs.admin.ch/bfs/en/home.html. (Accessed July 2018).
Simons, N.K., Weisser, W.W., 2017. Agricultural intensification without biodiversity loss is possible in grassland landscapes. Nat. Ecol. Evol. 1, 1136.
Smit, H., Metzger, M., Ewert, F., 2008. Spatial distribution of grassland productivity and land use in Europe. Agric. Syst. 98, 208–219.
Socher, S.A., Prati, D., Boch, S., Müller, J., Baumbach, H., Gockel, S., Hemp, A., Schöning, I., Wells, K., Buscot, F., 2013. Interacting effects of fertilization, mowing and grazing on plant species diversity of 1500 grasslands in Germany differ between regions. Basic Appl. Ecol. 14, 126–136.
Soussana, J.-F., Lemaire, G., 2014. Coupling carbon and nitrogen cycles for environmentally sustainable intensification of grasslands and crop-livestock systems. Agric. Ecosyst. Environ. 190, 9–17.
Stumpf, F., Keller, A., Schmidt, K., Mayr, A., Gubler, A., Schaepman, M., 2018. Spatio-temporal land use dynamics and soil organic carbon in Swiss agroecosystems. Agric. Ecosyst. Environ. 258, 129–142.
Sulla-Menashe, D., Kennedy, R.E., Yang, Z., Braaten, J., Krankina, O.N., Friedl, M.A.J.R.S., 2014. Detecting forest disturbance in the Pacific Northwest from MODIS time series using temporal segmentation. Remote Sens. Environ. 151, 114–123.
Svoray, T., Perevolotsky, A., Atkinson, P.M., 2013. Ecological sustainability in rangelands: the contribution of remote sensing. Int. J. Remote Sens. 34, 6216–6242.
SwissTopo, 2018. Federal Office of Topography. https://www.swisstopo.admin.ch/en/home.html. (Accessed July 2018).
Tälle, M., Deák, B., Poschlod, P., Valkó, O., Westerberg, L., Milberg, P., 2016. Grazing vs. mowing: A meta-analysis of biodiversity benefits for grassland management. Agric. Ecosyst. Environ. 222, 200–212.
Tasser, E., Tappeiner, U., 2002. Impact of land use changes on mountain vegetation. Appl. Veg. Sci. 5, 173–184.
Taugourdeau, S., Huguenin-Elie, O., Plantureux, S., Michel, N., Dumont, B., 2013. A Grass Use Intensity index to be used across regions and grassland managements. The role of grasslands in a green future: threats and perspectives in less favoured areas. In: Proceedings of the 17th Symposium of the European Grassland Federation, Akureyri, Iceland, 23–26 June 2013. Agricultural University of Iceland, pp. 397–399.
Weber, D., Schaepman-Strub, G., Ecker, K., 2018. Predicting habitat quality of protected dry grasslands using Landsat NDVI phenology. Ecol. Ind. 91, 447–460.
Wilson, J.B., Peet, R.K., Dengler, J., Pärtel, M., 2012. Plant species richness: the world records. J. Veg. Sci. 23, 796–802.
Wolberg, G., Alfy, I., 1999. Monotonic cubic spline interpolation. In: 1999 Proceedings Computer Graphics International. pp. 188–195.
Zaks, D.P., Kucharik, C.J., 2011. Data and monitoring needs for a more ecological agriculture. Environ. Res. Lett. 6, 014017.
Zeeman, M.J., Hiller, R., Gilgen, A.K., Michna, P., Plüss, P., Buchmann, N., Eugster, W., 2010. Management and climate impacts on net CO2 fluxes and carbon budgets of three grasslands along an elevational gradient in Switzerland. Agric. For. Meteorol. 150, 519–530.
Zeileis, A., Grothendieck, G., Ryan, J.A., Andrews, F., Zeileis, M.A., 2018. Package 'zoo'.
Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sens. Environ. 84, 471–475.
Zhou, G., Zhou, X., He, Y., Shao, J., Hu, Z., Liu, R., Zhou, H., Hosseinibai, S., 2017. Grazing intensity significantly affects belowground carbon and nitrogen cycling in grassland ecosystems: a meta-analysis. Glob. Change Biol. 23, 1167–1179.
Zhu, Z., Woodcock, C.E., Olofsson, P., 2012. Continuous monitoring of forest disturbance using all available Landsat imagery. Remote Sens. Environ. 122, 75–91.
Zhu, Z., Wang, S., Woodcock, C.E., 2015. Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. Remote Sens. Environ. 159, 269–277.