RESEARCH ARTICLE

Fine temporal resolution satellite sensors with global coverage: an opportunity for landscape ecologists

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Abstract

Context Open data policies and accessible computation platforms allow efficient extraction of information from remote sensing data for landscape research. Landscape ecology is strongly influenced by remote sensing, and the value of fine resolution temporal information for characterising landscapes is under-explored.

Objectives We highlighted the importance of temporal information extracted from remote sensing data gathered over a period of time for landscape research. A case study approach was used to show how time-series information can benefit the mapping of land cover and landscape elements in a heterogeneous landscape dominated by agricultural land use.

Methods We constructed four composite images of the study area, each incorporating different levels of temporal information. The images either represent a single date or summarise temporal information into single values as the median of spectral bands or vegetation indices. Random forest and *k*-means clustering methods were used to classify the images.

Results The overall accuracy of the landscape classifications ranged between 0.3 to 0.8, increasing substantially when including temporal information, for mapping both land cover and small landscape elements. Using temporal information and a RF-based classification it was generally possible to map crop and forest types. The size of landscape elements was overestimated, although the clustering model predicted elements close to their true size and complexity.

Conclusions The approach highlights the importance of temporal resolution for landscape ecology research. The easy-to-implement methodology offers an opportunity for landscape ecologists to increase the accuracy of landscape mapping and identify ecologically important landscape elements that might otherwise be missed.

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Introduction

Landscape ecology focuses on the study of spatial heterogeneity within the landscape and its associated implications for ecological processes (Forman and Godron 1986; Wu et al. 1997).

Remote sensing (further RS) data are a primary source of information within landscape ecology research, in particular for assessing changes in land use-land cover (further LUC) (Troll 1968; Estes et al. 1980; Groom et al. 2006; Lopez and Frohn 2017), and have provided an important source of landscape information for as long as aerial imagery has been available (Groom et al. 2006). Historically, the ability of landscape ecology to provide knowledge on the spatial heterogeneity of landscape features has been linked closely to advances in RS. In particular, landscape ecology has benefited from advances in the scales of measurement of different RS sensors. Within the context of landscape ecology, the scales of measurement are defined as grain size (resolution) and extent in space and time (Wu and Qi 2000). The sensitivity of landscape element mapping and detection to scale has been demonstrated, for example, by quantifying the response of mapped landscape elements and indices to changing grain size (Turner et al. 1989; Wiens and Milne 1989; Wu 2002, 2004; Corry and Laforteza 2007) and thematic resolution, which is the level of detail in a classification system (Bailey et al. 2007; Lechner and Rhodes 2016). Generally, these studies have demonstrated that no single scale is relevant to all ecological questions within a given landscape (Turner et al. 2001). Similarly, both “synthetic” and real case studies have demonstrated the importance of study area extent for research outcomes, especially for capturing dynamic events, such as animal movements or the spread of disease (Franzen et al. 2007; Gregorio et al. 2006). Determining an optimal grain size and areal extent for a given research problem has become a common task for studies in landscape ecology driven, in part, by technical limits to data processing and the computation of landscape indices.

Technical advances in recent decades and the availability of Big Data and related infrastructure have meant that debates on optimisation of study extent have almost been relegated to history (Crowley and Cardille 2020). Open-access data policies for satellite sensor imagery that operate beyond the visible

spectrum (e.g., Landsat, Sentinel-2) have meant that the information required to identify many landscape elements of interest in landscape ecology research is readily available. Similarly, cloud computing facilities such as Google Earth Engine have processing power and storage capabilities suitable for evaluating the full archives of satellite sensor imagery and sharing scientific knowledge readily (Gorelick et al. 2017).

The benefits of rapid developments in RS technology for landscape ecology, particularly for monitoring LUCC, have been recognised largely as being due to the increasing spatial resolution of the available data (Wickham and Riitters 2019). However, there have also been significant advances in the temporal and spectral resolutions of RS data. Aside from describing landscape transitions between two time periods (Singh 1989), fine-resolution temporal information can characterise additional landscape properties, increase the accuracy of landscape classification and increase thematic resolution, for example, through identifying management intensities within agricultural landscapes (Estel et al. 2018; Kolečka et al. 2018; Griffiths et al. 2019).

Classification of landscape features, especially vegetation features and agricultural landscapes, can benefit from an increase in temporal resolution as typically they are highly dynamic in phenology and can be subject to heterogeneous land use intensities over time; for example, multiple crop rotations within a year or variable grazing and mowing regimes. Such dynamism has important implications for landscape function and the support of landscape services such as biodiversity or carbon sequestration (Ali et al. 2016). In addition, agricultural landscapes often support fine scale landscape features such as single trees, hedgerows or tree lines (further landscape elements) that are essential features supporting biodiversity (Benton et al. 2003), but are not always detectable by satellite sensor imagery (O’Connell et al. 2013, 2015). The advent of Open Access medium spatial and temporal resolution satellite sensor imagery, potentially offers a solution to tackle the omission of those landscape features. In fact, the field of landscape ecology can, as in the past, benefit from advances in RS and a wealth of opportunities to better understand landscape scale processes through more detailed mapping of landscape patterns and the dynamics of these patterns.

Aims and objectives

In the context of a special issue examining how Landscape Ecology benefits from developments in other disciplines and vice versa, this paper aims to contribute to the scale debate in landscape ecology. Using an experimental case study involving a rural landscape dominated by agricultural land-use, we demonstrated the importance of time-series (further TS) RS data for characterising landscape heterogeneity in relation to LUC. We derived different images of the case study area and used different classification techniques to explore: (1) the benefit of temporal information for increasing the accuracy of mapping LUC, (2) the importance of temporal information for mapping fine scale landscape elements, and (3) the ability of temporal information to increase the thematic resolution of LUC mapping. We assess LUC using models trained to both a broad and a detailed classification nomenclature-level. At the broad nomenclature-level, we distinguished settlement area, cropland, permanent crops, grassland and forests, while for the detailed level those initial classes were further classified to separate intensely used crop rotation areas from permanent crops and grassland and broadleaf and coniferous forest within the forested areas. Further, we evaluated how RS TS information can increase the ability to detect fine scale landscape elements represented by vegetation features located outside forests.

Mapping landscapes using remote sensing data

Milestones of landscape research based on moderate resolution optical remote sensing data

The Landsat satellite sensors have gathered moderate spatial resolution data in the visible spectrum over almost 50 years representing the longest running terrestrial satellite sensor data record (Zhu et al. 2019) and are one of the most widely used sources of RS information. Since their launch, the Landsat sensors have been used to map LUC for a multitude of landscapes. Probably the first attempt to map cropland use, for example, dates back to 1975 (MacDonald et al. 1975). Since then, most landscape research related to change analysis has been based on two discrete states of a landscape (Singh 1989), usually snapshots of pre and post the event that causes

the LUC change. Landsat scenes have been used in this manner for local-, regional- and continent-wide studies. The US National Land Cover Database (Vogelmann 1998) and the European CORINE land cover project (Feranec et al. 2010) are probably the most widely used datasets of this kind internationally.

In 2008, an open access policy was applied to the Landsat archives and a surge followed in the use of medium resolution satellite sensor imagery and its temporal information (Zhu 2017). The opportunity to produce temporal stacks of Landsat scenes was now available to a wide variety of users and, thus, TS analysis was encouraged (Zhu et al. 2019). Production of regional, continental and global scale maps targeting a variety of research questions and time spans were no longer limited by costs of the data. Global forest land cover change maps (Hansen et al. 2013) or thematic maps of Central and Eastern Europe over different time periods of agricultural land abandonment (Griffiths et al. 2013) or forest disturbance (Potapov et al. 2015) are but a few examples. Being thematically focused, these maps provided unique outputs that outperformed the accuracy of spatial information of official, general data products and maps such as CORINE land cover or FAO statistical data. At the same time, many of the algorithms for processing satellite scenes effectively, such as cloud masking procedures (Zhu and Woodcock 2012; Zhu 2017), became openly available to the broader research community.

Another important milestone in landscape mapping was the launch of ESA's Copernicus satellite missions in 2015 and the open-access availability of Sentinel-2 optical imagery. The 10 and 20 m spatial resolution image bands of Sentinel-2 allowed the possibility to identify landscape features of ecological relevance such as linear vegetation elements or road networks, which might be hidden in the 30 m spatial resolution pixels of Landsat. Sentinel-2 imagery also provided a substantial increase in the temporal resolution of imagery compared to Landsat, with the opportunity to more precisely reconstruct seasonal changes in landscape features that become measurable with more frequent revisits.

In addition to the availability of imagery from different sensors, various initiatives have developed harmonised (enhanced temporal resolution) and fused (enhanced spatial resolution) virtual constellations. Several studies have demonstrated the spatial–

temporal benefits of, for example, harmonising and fusing MODIS and Landsat (Roy et al. 2008; Boschetti et al. 2015), or Sentinel-2 and Sentinel-3 (Wang and Atkinson 2018) for understanding landscape processes. Within the Sentinel-2 and Landsat domains, a harmonised constellation in Landsat native 30 m spatial resolution with dense temporal resolution was presented (Claverie et al. 2018), providing mutually calibrated tiled imagery with geometrical and atmospheric corrections. Multiple of those data resources are now available as “Analysis Ready Data” and stored on computing infrastructure (e.g., cloud computing). Such availability of pre-processed data and remote computation power allows users to focus on interpreting the outputs rather than on applying state-of-the-art methods of parameterization and pre-processing of imagery.

1.2.2 Usability of TS data and the shift in focus from spatial to spatial–temporal statistics.

The availability and accessibility of pre-processed RS data with sufficient TS information and cloud computing platforms was arguably the technological underpinning of a paradigm shift from change detection toward the continuous mapping of landscape changes (Woodcock et al. 2020a, b). Continuous mapping using TS is of particular importance for landscape ecology as it allows close reconstruction of the dates of landscape change events or the identification of non-abrupt transitions which occur over longer time periods. The TS of available imagery has allowed many trend analyses to focus on increasing understanding of changes within different LUC classes such as forest disturbance (Abdullah et al. 2019), urbanisation (Zhao et al. 2015; Deng and Zhu 2020) and changes in surface water (Pekel et al. 2016).

Aside from the identification of changes over space, TS information also helps identify those landscapes where the spectral reflectance may be influenced by atmospheric effects for a specific time period and falsely indicate a landscape change. Dense TS also allow fitting harmonic models that retrace the theoretical phenological cycle of a particular LUC. This approach also allows to detect break-points, which have been shown to be particularly useful for mapping abrupt changes in a TS, such as forest disturbance (Kennedy et al. 2010, 2018; Verbesselt et al. 2012; Zhu and Woodcock 2014).

Adaptation of temporal statistics for landscape mapping

TS of satellite sensor imagery can be aggregated to a single image output to allow the specific statistical characteristics of the TS to be summarised (e.g., median reflectance value). This procedure can also be helpful in removing artefacts or masked pixels which may occur in a single image within a TS (e.g., due to atmospheric effects). Such an approach is not new for remote sensing image classification and has often been linked to phenological indices. For example, Defries and Townshend (1994) extracted phenological summaries of the growing season (such as minimum and maximum NDVI or total greenness) to derive a global land cover map in the last decade of the twentieth century. This concept was furthered through the TIMESAT tool (Eklundh and Jönsson 2016) which popularised the extraction of multiple indices that characterise a phenological curve (e.g., beginning, end, amplitude of phenology over a growing season). Such indices allow classification nomenclature to move from simple land-cover assessment towards more complex, rule-based classification schemes related to land use and land-use intensity (Qader et al. 2016; Estel et al. 2018).

Using predefined indices, LUC information may be predicted through TS assessment using different machine-learning methods such as random forests (Breiman 2001; Breidenbach et al. 2010). Compared to other statistical methods, machine learning methods may be more flexible for classification of complex LUC classes as, for example, they can estimate non-linear relationships between LUC and indices and accommodate non-stationarity. As well as fitting nonparametric functions, machine learning methods can fit multiple decision trees and, thus, are less prone to overfitting compared to other methods that are based on a single decision tree (Maxwell et al. 2018).

Using TS together with clustering, an unsupervised classification technique which seeks homogeneity in spectral information, has also been found to be useful for classification of LUC (Kaufman and Rousseeuw 2005). Clustering techniques such as *k*-means clustering are capable of differentiating contrasting spectral information across pixels in their neighbourhood which is useful for a range of purposes, such as mapping small landscape elements (e.g., single trees,

hedgerows) which have high ecological value (Kolecka et al. 2018).

Experimental case study

We evaluate how remote sensing TS information can influence the mapping of landscape features using four LUC classification models, incorporating different levels of temporal information, in a case study landscape. The four models are termed: (1) single image model (Single Image, further SI), (2) growing season median model (Season Median Simple, further SMS), (3) growing season + phenology model (Season Median Advanced, further SMA) and (4) seasonal NDVI (normalised difference vegetation index) medians model (Seasonal Normalised Difference, further SND), and are detailed in “Data: satellite sensor images” section.

Study area

To test the impact of increased temporal resolution RS data for landscape ecology, we selected a 5×5 km study site located within the canton of Aargau in the central plateau of Switzerland (Fig. 1). The choice of study area was driven by data availability, and by the presence of heterogenous landscape structures that are

challenging to map. The study area is also in relatively flat terrain (534 m.a.m.s.l.) which allows sampling of land cover ground reference information that might not be influenced by spatial autocorrelation caused by terrain constraints (Ploton et al. 2020). The area is a traditional Swiss agricultural landscape with relatively high soil fertility, featuring small farms with a wide variety of crop and grasslands types. Moreover, in comparison to the rest of Switzerland, the area features a relatively large number of small landscape elements, such as single trees, hedgerows and lines of trees. These landscape elements provide biodiversity, aesthetic and cultural value, and farmers also receive subsidies for their maintenance (Arnaiz-Schmitz et al. 2018). Due to the small area, variability and complexity of the geometrical structure, accurate mapping of these elements based on optical satellite sensor data is challenging and often omitted on landscape maps despite the ecological importance of these elements.

Data: Satellite sensor images

Landscape classification was based on Sentinel-2 imagery pre-processed to Bottom of Atmosphere reflectance based on the sen2Cor algorithm implemented in the Google Earth Engine (GEE) platform (GEE library *COPERNICUS/S2_SR*). All image tiles with less than 70% cloud coverage captured within the

Fig. 1 Study area represented by (Level1) general and (Level2) detailed LUC classification. LUC on (Level1) represents: 0-roads, 1-settlement, 21-arable land, 22-permanent crops, 23-grassland, 30-forest, 33/40-shrubland or wetland. The LUC labels for (Level2) are listed in the Appendix. The coloured

frame on the LUC class legend represents the general classification level. *Source* OpenStreetMap contributors, 2017; Waser et al. 2017; Parcel-level farm statistics of Canton Aargau 2019

period April–October 2019 were included in the classification. The cloud removal model implemented in the GEE (GEE library *COPERNICUS/S2_CLOUD_PROBABILITY*) was also applied. This procedure uses deep learning semantic segmentation (Garcia-Garcia et al. 2017) to set the cloud occurrence probabilities within Sentinel-2 scenes (Zupanc 2017) and has been documented to outperform other cloud masking procedures (EO Research 2020). Additional scripts were used to mask shadows and snow coverage (see the linked GEE codes for more information).

We performed eight different classifications on the LUC dataset with two different classification models trained on four different images. The images were derived by embedding temporal information acquired from the Sentinel-2 bands into single images complemented with three different indices (NDVI, LSWI, EVI) commonly used to quantify vegetation phenology, as follows:

1. Single image (SI): the simplest representation of the landscape, whereby we selected a single clear-sky satellite sensor image representing the late June landscape. This model assumes that the heterogeneity of agricultural management practices is already visible within the satellite sensor image at this time of year.
2. The growing season median model (SMS) summarises reflectance of the selected Sentinel-2 bands and the defined vegetation indices (NDVI, LSWI, EVI) over the growing season (Table 1).
3. The growing season median and phenology statistics model (SMA) includes all the seasonal medians from the SMS model plus the phenological profile statistics; standard deviation, kurtosis, skewness and seasonal medians of the NDVI values over the TS, and different percentiles of the distribution.
4. The seasonal NDVI medians model (SND) summarises seasonal medians of NDVI for different time periods of the growing season into six bands.

Data: training and validation data

We classified the LUC based on two different levels of LUC nomenclature, a general LUC level with six classes and a detailed classification level with 26 classes (see Supplementary Material, *Tab. S1*). To develop the classification models we created a training dataset composed of multiple polygons representing homogeneous areas of the LUC classes at both levels of detail. The polygons were delineated manually from Google Earth Imagery available for the study site for August 2018 and assigned the LUC based on information from independent datasets, to limit interpreter bias. In agricultural areas the polygons were delineated according to the official parcel-level crop type data provided by farmers to cantonal authorities to obtain agricultural subsidies.

We used the reported parcel level agricultural data for the growing season of 2019 and included only those crops and grasslands that occurred with a total area of more than 1 ha, and on multiple agricultural parcels. 2018 was not considered as a reference year due to an extremely hot and dry summer that caused substantially lower than normal yields in agricultural areas (Reinermann et al. 2019), premature leaf shedding in forested areas (Schuldt et al. 2020) and likely spectral discrepancies between the reported and observed LUC classes. The spatial consistency between all the delineated polygons between the years

Table 1 Sentinel-2 image bands and phenological indices used to build the classification models

Model abbreviation	Model description	Image bands used in the model classification ^a
SI	Single image	Blue; green; red; nir; swir1; swir2; NDVI; LSWI; EVI;
SMS	Growing season median	Blue; green; red; nir; swir1; swir2; NDVI; LSWI; EVI;
SMA	Growing season median + phenology statistics	Blue; green; red; nir; swir1; swir2; NDVI; LSWI; EVI; NDVI _{5,25,75,85,95} percentiles of time series; NDVI _{standard deviation} ; NDVI _{kurtosis} ; NDVI _{skewness} ; NDVI _{spring} ; NDVI _{summer} ; NDVI _{autumn}
SND	Growing season temporal NDVI medians	NDVI _{DOY60-105} ; NDVI _{DOY61-105} ; NDVI _{DOY106-151} ; NDVI _{DOY152-196} ; NDVI _{DOY197-243} ; NDVI _{DOY244-288}

2018 (available Google Earth Imagery) and 2019 (Sentinel-2 scenes used to train the classification) was checked using the Sentinel-2 images. To differentiate broadleaf and coniferous forests we used the forest type map of Switzerland (Waser et al. 2017). In total, we generated 187 training polygons containing more than 20,000 valid Sentinel-2 observations. We used the same sample data to develop all classification models. We considered every sampled pixel as a unique observation. Since the study area represents a small heterogeneous landscape area, with limited variation in environmental variables such as climate and topography, any spatial autocorrelation in the training samples (polygons) should not influence significantly the model outcomes. Using the polygons to derive the training samples allowed us to sample the different LUC more densely and, thus, capture the full set of LUC classes.

Landscape elements

To explore the benefits of temporal information for landscape mapping we considered fine scale landscape elements such as linear vegetation structures and single trees within agricultural fields. To identify these landscape elements we used a 1 m spatial resolution vegetation height model (VHM) derived from leaf-on stereo aerial imagery captured over the period 2010–2016 for Switzerland (Ginzler and Hobi 2015; Ginzler 2018). We masked forest areas from the VHM map using forest polygons from Open Street Map (OpenStreetMap contributors 2017) with an outside buffer of 20 m to ensure that forest tree crowns at the edge of forests were not included in the analysis. Furthermore, we also masked out pixels of vegetation less than 3 m in height which removed areas of crops, shrubs and potential noise from the VHM dataset. The resulting 1 m spatial resolution raster was checked visually for consistency with the underlying Google Earth Imagery and aggregated to the 10 m spatial resolution of Sentinel-2 using the majority rule, and each raster patch was considered as a unique landscape element.

We assumed that a greater and more compact area of the present landscape elements will be captured more often with different classification models while the mapping accuracy of small and narrow landscape elements will largely differ among the models. Therefore, for each polygon of a landscape element,

we quantified its area and complexity. The complexity of each polygon was calculated as a perimeter–area ratio (S) defined as $S = P/3.54 \times \sqrt{A}$, where P is the perimeter and A equals area size. Scaled to a circle, relatively compact shapes have an S -ratio close to 1, while complex polygons have larger values (Shortridge 2004).

Accuracy assessment

To assess the accuracy of the outcomes we used the Swiss Land Use Statistics, a nationwide point sample of LUC information on a regular 100 m grid across Switzerland (Bundesamt für Statistik 2020). The regular sampling and independence of the Swiss Land Use Statistics from the training data eliminates the effects of spatial autocorrelation which is otherwise commonly present if validation data are derived from the training sample (Ploton et al. 2020). To match the nomenclature between the training and validation datasets we updated the points samples of Swiss Land Use Statistics on the agricultural plots and forested areas with the information extracted from the parcel level agricultural data and forest map, respectively. Points of the Swiss Land Use Statistics data located within the training polygons were removed from the validation dataset.

Two different accuracy measures were calculated to determine the quality of the classification outputs. First, we quantified the agreement between the classified map and validation dataset. We used an overall accuracy score and LUC class-based sensitivity and specificity rates. Secondly, we quantified the accuracies of the landscape element classifications using the area and complexity of each landscape element. The landscape elements were delineated using the VHM as described in the previous section and contrasted with the classification outcomes.

Classification techniques

Two different classification techniques were used to classify the landscape into LUC classes: random forest (RF) and k -means clustering (KM). The RF, as a machine learning technique, was documented to produce relatively high accuracy LUC classifications (Breiman 2001; Gómez et al. 2016; Belgiu and Drăguț 2016). The RF framework is easy to implement, available among different platforms and popular

within the RS community, especially for the classification of land cover. In the present case, the RF models were trained over the defined combinations of the Sentinel-2 bands and calculated phenological indices (description is provided in “[Data: satellite sensor images](#)” section). To fit the RF models we used the GEE platform (using the GEE library *ee.Classifier.smileRandomForest*) using the default parameter values (see Supplementary Material, *section S2 and S3*) except for the number of trees which was set to 300. Setting a large number of trees generally leads to more accurate classification (Belgiu and Drăguț 2016).

The KM approach was selected as another non-parametric method capable of clustering the pixels with a certain degree of homogeneity and contrasting its values with the neighbourhood. As the outcomes of classification are clusters and not the LUC classes, no training data are required. In this study, we used the WEKA SimpleKMeans algorithm (Witten et al. 2011) setting 26 clusters that correspond to the number of LUC classes in the detailed LUC maps. We also tested a greater number of clusters (52), assuming that a single class may be represented by multiple clusters. However, we did not find any increase in the resulting map accuracies. Other parameters of the WEKA SimpleKMeans algorithm were held constant (according to the GEE library *ee.Clusterer.wekaKMeans*, see Supplementary Material, Tab. S2). To assign the LUC classes to the clusters resulting from the model, we performed the classification using the original training data with the clusters as a single explanatory variable in the RF model. The RF model was preferred over other techniques for classification of the resulting clusters due to its consistency with the previously used RF modelling approach.

Results

Assessing the LUC

As documented in Figs. 2 and 3 the temporal information increased the accuracy of LUC classification at both the general and detailed classification levels. In both cases, the classification model based on the most complex SMA image data outperformed the other classification models. The SMA model obtained the highest accuracies in the RF and KM classification,

but very similar accuracies were obtained using the SND image. Overall, more accurate results were obtained by the RF models, with the SI model having the lowest accuracy, especially while applying the KM classification. Class-based accuracy assessment based on true positive rates (i.e., the ratio of correctly modelled presence of particular LC class) indicates forested areas and agricultural areas as the most accurately predicted classes, especially using the KM classification of the SMA image data (Supplementary Material, Fig. S4). Visual examination of the mapping outcomes (Fig. 2) and its comparison with the original map (Fig. 1) also suggests that the TS information increased the compactness of the mapped areas of the different LUC classes, particularly visible in the different types of forest or settlement structures.

Landscape elements

The classification models using TS information resulted in higher accuracies for mapping landscape elements (Fig. 4). Especially using the SMA and SI image datasets it was possible to map landscape elements with different complexities. In the general (Level1) model most landscape elements were mapped using the KM, which also tended to inflate the presence of landscape elements, especially those with greater complexity. On the other hand, the SMS and especially the SI image datasets failed to characterise the landscape elements.

As with the general classification, the detailed land-cover mapping models were able to map those landscape elements with medium complexity (Fig. 4). Again, the TS information at different classification levels was essential for the accurate mapping of landscape elements, while the SMS and SI image datasets were commonly insufficient for mapping the landscape elements. The KM models using TS information were the most accurate with respect to preserving the area and complexity of landscape elements, and were the most accurate models for capturing small and complex landscape elements.

Discussion and conclusion

Remote sensing data have long been integral to landscape ecology and advances in remote sensing and related processing techniques have influenced the

Fig. 2 Classification outputs using the RF and KM models on images with different time-series information (SI, SMA, SMS, SND) using general (Level 1) and detailed (Level 2) classification nomenclature. Values in brackets represent the overall accuracy of the classification models. General LUC

nomenclature: (10) settlement/sealed areas, (21) arable land, (22) permanent crops, (23) grassland, (30) forests, (40) shrubland or wetland. For the detailed LUC classification refer to the Fig. 1 or Table S1 in the Supplementary Material

Fig. 3 Overall accuracy rates of the different classification models (RF, KM), different input image datasets (SI, SMA, SMS, SND) and different classification nomenclatures (Level1, Level2). Note that the KM outputs were post-classified using the RF model

field significantly over its history. Multiple review studies (Gómez et al. 2016; Woodcock, et al. 2020a, b; Crowley and Cardille 2020) showed that access to big data computation platforms and open-data policies are significant milestones for landscape ecology given the new opportunities to assess landscape patterns and infer processes. These advances have allowed small scale (i.e., large area) mapping tasks to be performed at high levels of accuracy in a fraction of the time previously required. In addition to these technical advances, shared and cloud computing platforms have brought analysis-ready-data and state-of-the-art analytical methods closer to a wide research audience, shifting the focus of research tasks from pre-processing remote sensing data (Gorelick et al. 2017) to the ability to monitor readily spatial and temporal landscape heterogeneity and dynamics. Using common input data also helps to obtain a better overview of the applicability of those data and expected outcomes (Crowley and Cardille 2020). In this paper, we aimed to contribute to discussions on the importance of scale in landscape ecology by highlighting the importance of temporal information for landscape classification. We showed that embedding seasonal variability enables mapping significantly more fine scale landscape elements and also better captures the complexity of landscapes. Temporal information also allows increases in the thematic resolution of landscape

classifications in the sense of the detail in the classification nomenclature. We believe that TS RS data offer significant benefits to the landscape research community since approaches, such as those demonstrated in this paper, are relatively easy to implement and the required TS metrics can be calculated using Open Access data and through an open cloud computing platform. The training data and code required to run the classification models are supplied in the Supplementary Material (S3).

The temporal information relevant for LUC classification could be represented as a state in a single date image by choosing a date when the landscape elements of focus are best represented (e.g., the most recent image), or by a TS of images that spans a particular period in time (Ghamisi et al. 2019). We compared both: single date image and images that aggregate temporal information, and used two different classification modelling approaches to demonstrate how the inclusion of temporal information influences the accuracy of landscape mapping.

Our results showed that for commonly used, coarse LUC classes, temporal information consistently increased the accuracy of LUC classification. Temporal information allowed the models to more clearly distinguish between phenologically “stable” LUC classes such as roads, forests and permanent grassland

Fig. 4 Ability of the different land cover classification models (Level1, Level2) to identify landscape elements with different area (ha) and complexity (compact, complex, medium) within different imagery (image). The black vertical line represents the area quantified on a different complexity level with the ground reference data and the dots represent the area classified correctly

and phenologically dynamic LUC classes such as arable land and managed grasslands.

Using two different modelling approaches, RF classification models resulted in much higher accuracies of land cover classification than KM classifications especially for agricultural areas. These higher accuracies with RF models are likely due to the high heterogeneity of LUC intensities within agricultural fields, embedded in a single LUC class. Such heterogeneity can be more effectively captured with the non-stationary RF model (Belgiu and Drăguț 2016). The KM approach more accurately captured the heterogeneity of agricultural areas in the detailed LUC

with the model. Points closer to the vertical line indicate more accurate capture of the landscape elements (i.e., highest true positive accuracy), while the bars beyond the vertical line indicate greater presence of the landscape elements in the resulting map than in reality (true + false positive accuracy)

classification than in the general classification. However, likely due to the similarity of different crops, the KM model misinterpreted the LUC classes and resulted in lower accuracy compared to the RF approach. Using the RF approach for detailed LUC class assessment, the complex image stack (SMA) and the seasonal phenology (SND) models provided the most accurate classification maps. Overall, the most biased RF model using a single image (SI) was almost as accurate at distinguishing the LUC than the best KM model. This result demonstrates the importance of the modelling procedure, for assessment of LUC classes.

The inclusion of temporal information allowed the detection of small woody landscape elements that were not found in the single-date image, despite no change in the spatial resolution. The reason for the higher accuracies is the increase in the contrast between the pixels of the small woody elements and their neighbourhoods related to the implementation of the TS. Mapping of these elements defines the composition and configuration of the landscape which are core concepts in landscape ecology (Turner et al. 2001). Small woody landscape elements serve multiple ecological functions including attracting different plant and animal species, protection of natural resources (Baudry et al. 2000) and connectivity of fragmented landscape patches (Bennett 2003). Thus, many studies that focused on these features used fine spatial resolution RS imagery like aerial photos or laser scanning data to map landscape elements such as single trees and hedgerows (Tansey et al. 2009; Hellesen and Matikainen 2013). As demonstrated with models of biomass or woody vegetation outside the forest (Price et al. 2017) the landscape elements may be extracted from a vegetation height model (VHM) (Ginzler 2018), as used in this study to delineate the reference data. Producing maps of landscape elements is generally costly with respect to input resources (e.g., laser scanning data) or, in the case of manual delineation, time needed to produce these maps. Medium spatial resolution imagery coarser than 5 m spatial resolution, is commonly considered to be inadequate to map small landscape features (O'Connell et al. 2015). The TS information, as included in our LUC models, benefits the detection of small features by capturing the seasonality of the landscape that allows contrast with surroundings. The contrast in seasonality of landscape elements was highlighted especially by the KM models which consider neighbourhoods by developing clusters. However, the accuracy of the KM models used for mapping different LUC classes was low, which is likely related to the limited generalisation capabilities of the KM classification (Uhl and Leyk 2020). Thus, a combined approach of using the KM models for landscape elements and a RF model for the overall classification could be considered to provide more accurate landscape mapping.

We demonstrated that TS RS imagery can increase the spatial and thematic accuracy of LUC maps. While enhancement of accuracy with TS is known from the

studies that analyse the temporal changes between different time horizons or rule-based classifications based on TS data, the advantages for producing LUC maps of landscapes with heterogeneous LUC intensities have been little explored previously. Spatial and thematic resolutions, in addition to the composition and configuration of the landscape, form core concepts in landscape ecology as they define the spatial pattern of the ecological phenomena (Wiens 1997). Moreover, both spatial and thematic resolutions interact and should both be considered for mapping landscapes (Lechner and Rhodes 2016). Current availabilities in data and technical infrastructure support enhancing those core concepts.

Spatial scale has become a standard topic for discussion and debate in landscape ecology mapping since the last decades of the twentieth century. Besides spatial scale, one should also consider temporal information and scales, for example, as we documented in this paper its influence on the accuracy of landscape mapping. Providing adequate training information is especially important when many of the most accurate modelling techniques are often combined with only small amounts of information for model fitting and parametrization. This is especially true for the many different machine learning and deep learning models where the quality, as well as quantity, of training data is recognised as essential to providing accurate model outputs (Sambasivan et al. 2021).

We used the opportunity of this special issue, targeted on the potential benefits to landscape ecology of developments in other disciplines, to raise awareness amongst ecologists of the importance of, and now widespread availability of, TS data and especially TS RS data. Researchers are encouraged to adopt the available approaches for TS landscape classification, such as those documented in detail in the Supplementary Material S3, and to use the available thematically detailed RS data for training these classification models. Researchers can use the available computation platforms to enhance their landscape mapping products and, thus, increase the quality of their landscape research.

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