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RESEARCH ARTICLE

# How fast do landscapes change? A workflow to analyze temporal changes in human-dominated landscapes

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**Abstract**
*Context* Anthropogenic activities alter natural habitats, with impacts on species that live in human-modified systems. Often abrupt, anthropogenic influences not only alter the availability and distribution of suitable habitats for species, but also the ability of species to perceive variations within the landscape. Researchers studying the drivers of species distribution and behavior often use "static" land-cover maps as descriptors of habitat, which are most typically characterized at predictably cyclical seasonal scales. Changes that occur over shorter temporal scales are rarely quantified, and there is a lack of understanding of how landscapes change within seasons.

*Objectives* We propose a generic work-flow to identify the temporal scales at which changes in land-cover patterns can be detected within a landscape.

*Methods* We use easily calculated landscape metrics such as patch area, inter-patch distance (ENN) and shape complexity (SHAPE), obtained using high-resolution satellite imagery. We conducted pairwise comparisons for each metric and LULC class separately, at temporal scales corresponding to 15, 30, 45 and 60-day intervals, using a case study from central India.

*Results* We observed that changes in landscape structure and in land-cover classes can be detected even at a 15-day time period in human-dominated landscapes. In our case-study, agricultural fallows showed the highest proportion of change-points. The grassland class was the most stable across metrics and time-scales. Among metrics, SHAPE was the most stable and ENN was the most dynamic, indicating

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that while patch structure remained relatively stable, patch configuration changed more rapidly.
*Conclusions* We suggest that when studying animal resource use and movement, particularly in anthropogenically modified systems, matching the temporal resolution of landscape-level data to animal movement data is critical, as broad-scale data may miss key triggers of animal response.

**Keywords** Animal movement · Landscape metrics · Patch dynamics · Temporal scales · Remote sensing · Landuse/landcover classes · Movement ecology

## Introduction

Human activities such as agriculture, urbanization, industrialization and energy production are major drivers of land-use and land-cover (LULC) change globally. These anthropogenic footprints alter the availability and form of natural habitats, and directly impact almost all types of life on Earth at multiple spatial and temporal scales. Anthropogenic change to the environment can often occur in abrupt ways. For e.g., new buildings can be constructed within months, and monoculture of crops convert large land areas within weeks. Such changes to the landscape not only alter the availability and distribution of suitable habitats for species, but also their ability to predict changes in the landscape. Many species, however, seem to continue to persist in human-modified landscapes, despite continuous anthropogenic activity (Verdade et al. 2014; Chapron et al. 2014; Carter and Linnell 2016; Katna et al. 2022). The responses of such species to anthropogenic factors can also occur at multiple spatial and temporal scales, depending on the distribution of preferred resources (Cagnacci et al. 2010; Dechen Quinn et al. 2013; Northrup et al. 2016), and the scale at which these animals perceive their surroundings (González-Megías et al. 2007).

Understanding the factors and scales that drive animal responses to environmental variation has been a central theme in animal ecology (Cagnacci et al. 2010), and is the basis for the field of movement ecology (Nathan et al. 2008). One of the four components of the movement ecology framework is the influence of environmental factors, or external factors, on the movement and resource use of individuals. Landcover patterns within an individual's home range are intrinsically linked to the ecological processes taking place within a landscape (Uuemaa et al. 2013). Spatially, resource distribution (e.g., forage and cover) arising due to land-cover patterns has been found to determine habitat use by species. For example, in central New York State, USA, white-tailed deer select areas with highly aggregated patches of suitable land-cover types, and show smaller home range sizes, even in highly heterogeneous regions, provided the suitable landcover patches were accessible (Quinn et al. 2013). Changes in naturally occurring temporal cycles, such as seasons, intersect with the activity of humans to further shift the landscape for species. For example, in an agriculture matrix in North Carolina, USA, coyotes show seasonal variations in habitat use, where they use agricultural fields throughout the day in summer months but only during the night in winters, a pattern primarily associated with the availability of pre-harvest resting sites (Byrne et al. 2014). The effects of both spatial and temporal variations in LULC patterns propagate across trophic levels (Killengreen et al. 2011), and can either have short-term impacts that are cyclical, or long term impacts that are more permanent (Lambin et al. 2000; Gurarie and Ovaskainen 2011).

Landscape structure and LULC patterns are usually quantified using data obtained from remotely sensed satellite imagery (Fichera et al. 2012), often through the use of 'landscape metrics' (Cushman et al. 2008; Hesselbarth et al. 2019). These metrics are defined based on the spatial arrangement of pixels or LULC classes, and can be quantified at the patch, class, or landscape level (Narumalani et al. 2004). In general, metrics related to patch size, shape, edge and spatial aggregation have been most widely used in studies examining spatial and temporal variations in landscape structure and their effects on biodiversity (Kie et al. 2002; Lausch 2002; Bielsa et al. 2005). For example, the metric 'Euclidean nearest neighbor distance', indicates the proximity between patches of the same landcover class (Cushman et al. 2008). This could be particularly important when studying movement of habitat specialists. Patch size (or mean patch area per landcover class) is another widely used metric for community-level ecological studies because it directly indicates the availability of the landcover type for animals that depend on it (Narumalani et al. 2004).



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Researchers interested in the drivers of animal behavior have often used temporally "static" maps of LULC as descriptors of habitat. These LULC maps are generally derived at annual or seasonal scales, and may be too coarse to capture short-term changes, particularly in rapidly changing landscapes (Meentemeyer and Box 1987). Changes that occur over shorter temporal scales are rarely quantified, and there is a lack of understanding of how landscape changes within seasons influence animal distribution (Bertrand et al. 2016). Vegetation structure within a landscape can change at intervals shorter than typically-defined seasonal cycles, particularly in more heterogeneous ecosystems, such as human-dominated landscapes characterized by a mosaic of natural and anthropogenic LULC types (Bertrand et al. 2016). When using highly dynamic animal movement data with relatively broad-scale data on landscape structure, variations in movement or resource use patterns will often not match the temporal scales of change of the external factors being studied, leading to a gap in understanding the actual processes that may be driving these animal movement decisions. For example, at the shortest temporal scales, resource use and the corresponding movement patterns are an immediate response to changes in resource or risk within the individual home range (Gurarie and Ovaskainen 2011). Longer time-scales are more suited to studying migrations or broader patterns in home-range size or resource utilization of individuals (Ullmann et al. 2018). Furthermore, although some studies use fine-scale temporal data for environmental correlates (May et al. 2010; Moorter et al. 2016; Northrup et al. 2016), there is seldom a validation to determine if the environmental variation is actually detectable, particularly for highly dynamic human-dominated landscapes. Developing an understanding of the complex interactions between landscape structure and animal resource use is important when assessing how this landscape heterogeneity (also often referred to as fragmentation), particularly in human-dominated landscapes, affects animal movements (May et al. 2010).

As the effects of scale and degree of heterogeneity within a landscape varies with species (May et al. 2010) and also the behavior being studied, in landscapes that witness higher levels of temporal heterogeneity, such as human-dominated landscapes, activities such as crop growth, harvesting and sowing lead to rapid changes in resource distribution within seasons. Such changes directly impact species that persist in these areas. This temporal aspect of variation in habitat due to underlying anthropogenically-influenced vegetation dynamics has often been neglected in landscape ecology (Vasseur et al. 2013) as well as in animal ecology (Mueller et al. 2011). When examining the effects of LULC patterns on animal movement, it is important to first identify the relevant scales at which temporal changes occur in the landscape (May et al. 2010; Benson et al. 2015).

Utilising commonly used and easily calculated landscape metrics, we propose a generic work-flow to identify the temporal scales at which detectable changes in LULC patterns occur within a landscape, and use a specific set of LULC classes and metrics as an example. We emphasize that the selection of these scales should correspond to the species being studied and the specific objectives, along with the vegetation or habitat type. In order to examine patterns across a range of LULC classes, we selected a landscape that consists of a matrix of native and anthropogenically modified LULC classes. We expected that LULC patterns within a landscape will change at scales that are much shorter than seasonal scales and will vary with the vegetation type and other environmental or economic conditions. Using classifications of high resolution satellite imagery at different interval periods, ranging from 15 to 60-day cycles, we calculated landscape metrics and the frequency of changes in landscape metrics describing LULC. We expected that the more natural patches of the landscape (e.g., native savannah) would be more stable across time with detectable changes at the seasonal intervals, whereas the anthropogenic LULC classes (particularly agriculture) would show the highest variation at finer temporal scales. Identifying the scales at which LULC patterns change within a heterogeneous landscape allows for a better matching of fine-scaled animal movement data to determine how animals are responding to such changes.

## Methods

### Study site

This study site is located in the rural and peri-urban areas of Baramati, Daund and Indapur sub-divisions (Talukas) of Pune District, Maharashtra in West-Central India (Katna et al. 2022). A study area of ~611



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km$^2$ in this landscape was selected as it has a mix of naturally occurring native savannah habitats and several anthropogenic LULC classes such as agriculture, poultry farms, linear infrastructure, managed plantations, and industries. This area is also the focus of a multi-species movement ecology project (Katna et al. 2022).

For assessing the temporal scales of changes in LULC patterns, we selected the period from November 2017 to May 2019. We obtained one high-resolution (10 m) satellite imagery (Sentinel 2 -https://www.sentinel-hub.com/explore/eobrowser, last accessed 31/10/2020) for every 15-day period. For periods with extensive cloud-cover, cloud-free images for the nearest date were considered. There were several 15-day intervals, particularly during the monsoon months, where no cloud-free images were available, and these account for some gaps in the data. Overall, we used a total of 29 images for the study period.

## Image classification

The image classification process followed the workflow described in Fig. 1(Part A). In order to obtain the patch-level landscape metrics, we first conducted image classification using object-based image analysis under the 'segmentation' module of TerrSet 18.31 (Eastman 2015). We included the NDVI band during the classification stage (Liu and Yang 2015), along with the green, red and NIR bands, to improve the object segmentation process.

We assigned six categories to LULC classes (water, built, agriculture, fallow, grassland and plantation), and combined irrigated and rainfed crops into one 'agriculture' class as classifying different agriculture types was outside the scope of this study. The 'plantation' class consisted of tree plantations managed by the state forest department. We conducted field-verifications of 80 randomly-generated ground control points within the study area boundary to evaluate the accuracy of the classified images. Once generated, the same ground control points were used for all subsequent field-verifications. As visiting these ground control points was a very time-intensive exercise, and was also limited by weather conditions and access to the locations, this could only be done in specific months. However, we ensured that the field-verifications were distributed across the study duration. The accuracy assessment was then conducted using the ERRMAT module of TerrSet 18.31, which generates an error matrix using user's and producer's accuracies for each LULC class from the

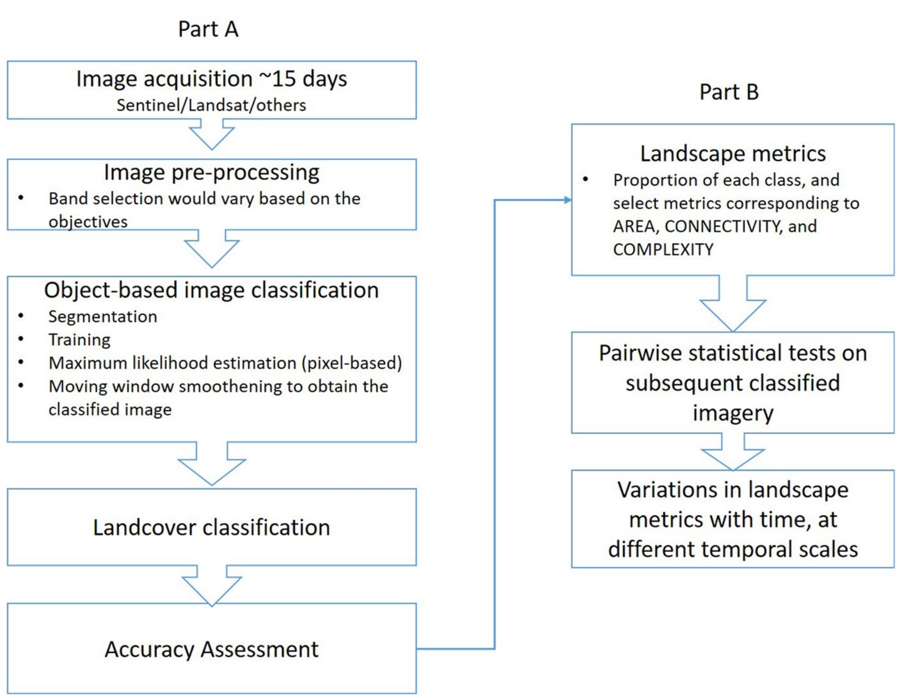


**Fig. 1** A generic workflow to identify the temporal scales at which changes occur in the landscape structure. The left column corresponds to image classification, and the right column corresponds to the analyses of the landscape metrics. Similar to the band selection process during image pre-processing, the level of landcover classification and the choice of landscape metrics would vary based on study objectives and region



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classified and ground-truthed values corresponding to the ground control points. In addition to the accuracy assessment, the Relative Error of Area (REA) was calculated (Shao and Wu 2008) for agriculture, fallow and grassland classes. The REA is an index that corresponds to the uncertainty in LULC classification using remotely-sensed imagery (Shao et al. 2003). It combines the user's, producer's and overall accuracy to provide a robust estimate of the degree of over- or under-estimation of the LULC classes.

### Data analyses

In order to identify the number of instances where changes occurred in landscape metrics between two subsequent images, we conducted pairwise comparisons for each metric and LULC class separately (Fig. 1Part B). We assigned each image a unique code. Among the six LULC classes, we focused on agriculture, fallow and grassland in this study, as these are expected to be the most dynamic among these, and constitute ~91% of the study area. We then calculated patch-level landscape metrics for each LULC class and image (Cushman et al. 2008; Lechner et al. 2013). As metrics under similar categories are often highly correlated to each other (Bolliger et al. 2007), we selected one metric each under the categories of 'area/density/edge' (patch area, PA), 'isolation/proximity' (Euclidean nearest neighbor, ENN), and 'shape complexity' (SHAPE). Isolation and proximity indices also offer information on patch connectivity, and thus, 'connectivity' indices were not obtained separately.

Thus, by using PA, ENN and SHAPE, we were able to obtain information on patch sizes, the distribution of patches within the landscapes and the complexity for each patch. These metrics were obtained using the "*landscapemetrics*" package (Hesselbarth et al. 2019) in R Studio 1.3 (R Core Team 2019). After obtaining the landscape metrics for the three LULC classes for the 29 images, we created three datasets, one for each LULC class, with each dataset containing patch-level metrics and the corresponding unique image code. Using the unique code as the grouping variable, we conducted pairwise Wilcoxon tests on the three LULC classes, using Bonferroni correction to control for the group-wise error rate (Kie et al. 2002). We conducted these tests at temporal scales corresponding to 15-, 30-, 45- and 60-day intervals, and examined the number of times significant changes occurred for each class and temporal scale. Each pair, where the difference in the metrics of two consecutive images was statistically significant, was termed as a 'change-point'. Both the number and proportions of change-points were obtained.

## Results

### LULC classification

Approximately 60% of the study area consisted of LULC classes that were extensively managed by humans. Across the study duration, the proportions (across 29 images, corresponding to the period between November 2017 and May 2019) of agriculture (0.11–0.28), fallow (0.23–0.42) and grassland (0.32–0.43) did not vary substantially (Fig. 2).

### Accuracy

Using object-based image classification methods, we were able to accurately differentiate between LULC classes in the study area, as evidenced by the user's and producer's accuracy values (overall mean producer's accuracy of 85% and an overall mean user's accuracy of 87%). While this was true for a majority of the images, there was some mixing of patches between fallow and grassland, owing to similarities in spectral signatures during these periods. This resulted in an overall lower producer's accuracy for the fallow class, as some fallow patches were classified under grassland. Despite this, the lowest producer's accuracy for fallow was 0.68, which is expected considering the actual intermixing of fallow and grassland patches within the study area. The mean producer's accuracies for agriculture, fallow and grasslands were 85% ± 7%, 76% ± 8% and 93% ± 3%, respectively, whereas the mean user's accuracies were 88% ± 11%, 88% ± 4%, 84% ± 3%, respectively. The mean REA value for the grassland class was positive (10.69) and those of the agriculture and fallow classes were negative (-2.508 and -18.285, respectively), indicating that the grassland class was slightly overestimated while the other two classes were slightly underestimated in their area.



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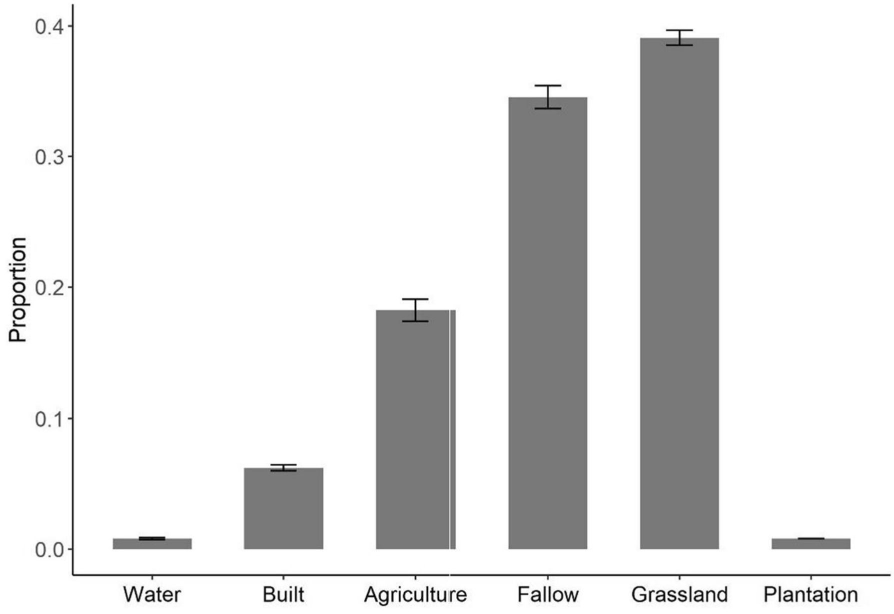


**Fig. 2** Proportions (mean ± SE) of the six LULC classes in the study area over an 18-month period from November 2017 to May 2019

Identifying temporal scales of change

We identified the number of change-points for the selected metrics (and LULC classes and their corresponding proportions (Fig. 3). Proportion of change-points for the anthropogenic LULC classes ranged between 11% and 46%. At the shortest (15-day) time-scale, fallow had the highest number and proportion of change-points for the PA and ENN metrics (Fig. 3). For SHAPE, at the 15-day scale, the number of change-points was highest for agriculture, followed by fallow and then grassland (Fig. 3). Thus, our results showed that change-points can occur in the LULC classes even at the 15-day scale.

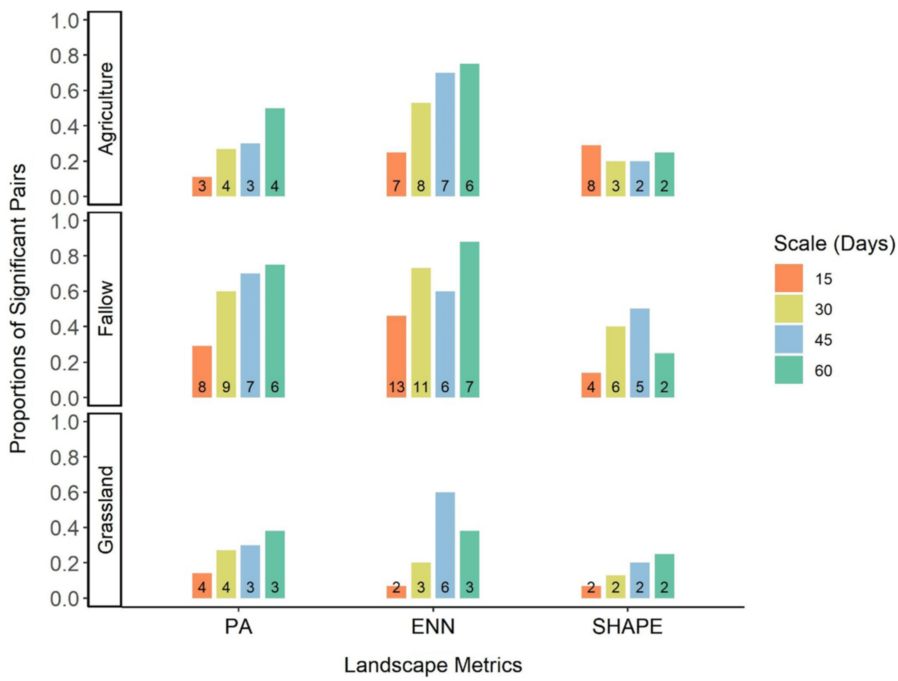


**Fig. 3** Proportion of change-points for the three LULC classes at different temporal scales. Grassland was the most stable LULC class with fewest changes, and fallow showed the most changes. Among landscape metrics, ENN captured more changes than PA and SHAPE. Numbers within each bar denote the number of change-point



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At the 30-day scale, fallow had the highest number and proportion of change-points, across all three landscape metrics. The grassland class showed the lowest number of change-points at the 30-day scale for ENN and SHAPE, but showed an equal proportion of change-points as that for agriculture in PA (Fig. 3).

However, a different pattern was observed at the 45-day scale. The number and proportions of change-points were similar for all LULC classes in ENN (Fig. 3), whereas agriculture and grassland had the same number of change-points for PA and SHAPE, which were lower than those of fallow.

At the longest temporal scale that we analyzed (60-day interval), the grassland class showed the lowest numbers and proportion of change-points across all three metrics and SHAPE had the lowest proportion of change-points among the three metrics and LULC classes. It is important to note that these change points did not occur together in time (see Supplementary File 1), i.e., the significant pairs between each subsequent image did not occur together for the three LULC classes across the three metrics.

## Discussion

Advances in satellite and remote sensing technologies have enabled researchers to now obtain data at very high temporal resolutions (e.g., Sentinel-2 has a rotation period of 10 days). Recent developments in analytical tools for satellite imageries (GEE, packages in R, proprietary software such as TerrSet) have also eased the processing effort required to obtain fine-scale data on environmental parameters and landscape structure from remotely-sensed images. In this study, we provide a generic work-flow (Fig. 1) to examine changes in landscape structure across different temporal scales. Using standard landscape metrics, our aim was to identify the shortest scale at which changes in the landscape structure could be detected. Our study site, characterized by a matrix of human and natural landcover patches, serves as a challenging test case to examine temporal variations in LULC patterns. Human-dominated landscapes undergo rapid temporal variations in LULC patterns due to activities such as agriculture. Variations in LULC patterns result from the interplay between environmental, biotic, economic, political and social factors (Turner 1989). Thus, accurately identifying LULC patterns and the scales at which changes occur is important when studying the patterns of habitat utilization by species present in the landscape (Shao and Wu 2008). As expected, the proportion of change-points and the period of their occurrence varied between each LULC class and metric. The generic workflow proposed as a part of this study is targeted towards identifying the temporal scales at which changes in landscape structure, particularly in heterogeneous systems (mostly human-dominated landscapes), can be detected. It should be noted that the same process can be applied to various landscapes.

Overall, the proportion of change-points tended to increase with increasing temporal scales across metrics and LULC classes. We found that the likelihood of detecting landscape change at the 60-day scale was higher than at other scales, which was expected given that this scale, and scales larger than 60 days, correspond to seasonal changes. Seasonal changes in LULC patterns and their interactions with ecological processes are well-documented and most readily incorporated into ecological studies (Katna et al. 2022). However, for actively managed land cover types, changes in the metrics of LULC were also detected at the 15- and 30-day scales. Human-dominated landscapes often undergo variations in vegetation structure more rapidly than relatively less-disturbed ecosystems (Fischer and Lindenmayer 2007), where the matrix is expected to remain stable at shorter temporal scales.

Given the diversity of crop types, cropping cycles and variation in crop growth rates we would normally expect the agriculture class to be the most dynamic. However, due to high computational and time requirements, we had clubbed various crop types in to one omnibus agriculture class. Likely because of this, the fallow class was the most dynamic, with the highest number and proportions of change-points at almost every time-scale (Fig. 3). This could possibly also be due to frequent shifts of an LULC patch between fallow and agriculture, as our study area also has seasonal crops and to a minor extent because of classification accuracy. The higher values for ENN and PA for fallow also indicate that fallow land parcels may be used for agriculture at specific weather conditions/seasons and to varying extents, i.e., converting only a proportion of a fallow patch to agriculture. Additionally, some land parcels that may have been left fallow for several years may have been re-used for cropping



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during the study period (this was also observed by AK and ATV during fieldwork), resulting in frequent changes to the landscape structure. By contrast, grasslands are not actively managed habitats, and thus showed the highest stability compared to agriculture and fallow landscapes. The proportion of change-points for grassland increased with decreasing temporal resolution for all three metrics, except at the 45-day scale for ENN. Being the most stable class, this was expected as changes in such LULC classes will be visible only at relatively longer temporal scales (e.g., seasonal). Even in cases where the proportions of change-points were similar between LULC classes for a particular metric, the change-points across LULC classes did not occur at the same points in time, indicating that different classes follow different variation patterns across time.

Landscape structure can be affected by a combination of anthropogenic (agricultural activities, grazing, land management, developmental activities) and natural factors (climatic events, weather, vegetation growth cycles) (Lausch et al. 2015; Kumar et al. 2018). The patterns observed in our study site could primarily be due to differences in plant growth rates within crops and between crops and natural vegetation and differences in land management. This observation is important as it suggests that because LULC types vary at their individual pace, the overall landscape is in a state of constant change in terms of landscape structure. These effects can vary with the LULC class and metric selected for analysis, resulting in different rates and timing of changes across classes on the same landscape matrix. Variable patterns of LULC change can impact space use or movement decisions by species that use a combination of classes for different purposes (e.g., resting or foraging) or for different life stages (Benton et al. 2003).

To a smaller degree, the interpretation of these results would also depend on classification accuracy, which is affected by several factors, including the landscape pattern and the algorithms used (Lechner et al. 2013). The uncertainty, or error, in classification increases with an increase in landscape heterogeneity, and it is often very difficult to achieve a very high classification accuracy (< 90%) in heterogeneous ecosystems (Lechner et al. 2013). Therefore, in such cases, it is important to be aware of the limitations of the classification process itself, and to reduce the error to the extent possible. In our case-study, the REA values showed that grassland area was overestimated in general. Further improving our classification accuracy would have therefore resulted in a decrease in the grassland area (the most stable class) and an increase in the more dynamic agriculture and fallow classes, which would have resulted in an increase in areas with a higher frequency of change-points. Thus, indices such as REA can be used to understand the extent of uncertainty when using remotely sensed imagery to quantify landscape structure.

The temporal trends of change also varied between the landscape metric selected, which collectively describe very different characteristics of the landscape. We found SHAPE to be the most stable of the three metrics, showing the fewest changes across different time intervals, whereas ENN showed the most changes. PA was the only metric that showed a consistent trend across all LULC classes with an increasing proportion of change-points with decreasing temporal resolution, whereas SHAPE showed no particular trend among the three LULC classes. This indicates that patch sizes and shapes change at relatively longer temporal-scales, but inter-patch distances show greater changes at shorter temporal scales. For animals on this landscape, such a landcover change pattern indicates that although the availability of resources may be stable, connectivity of suitable patches may affect access to these resources.

The advancement in animal tracking technologies has meant that animal movement data is now available at temporal resolution as fine as 1 Hz, yet the underlying environmental and landscape variables are often measured at much longer temporal scales, typically months (Bevanda et al. 2015). For species that respond to changes in landscape structure at much finer temporal scales, using landscape structure data at substantially coarser scales would not adequately capture the potential drivers and predictors of shifts in animal movement. For example, when examining home-ranges of the mesocarnivore guild in central India, we found that seasonal scales were not sufficient in identifying variations in resource selection (Katna et al. 2022). Additionally, the results of this study showed that across LULC types and metrics the possibility of detecting a change at a 60-day scale is expectedly high, but changes were also detected at 15-day scales. Therefore, it is important to match the temporal scales of the environmental factors with that of the movement data in order to develop a more



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accurate understanding of the ecology of species inhabiting such landscapes.

Landscape structure is strongly linked to the underlying ecological process and species survival (Lausch et al. 2015), and rapid changes in landscape structure have a more profound impact on resource availability within human-dominated landscapes than in more homogeneous or contiguous landscapes. Therefore, understanding how rapidly changes occur in human-dominated landscapes becomes important, as an increasing number of species would experience fast, and often unpredictable variations in resource availability. Frequent changes to inter-patch distance also increase movement costs (e.g. energy, time, risk) for animals that may need to travel farther to access resources (Baguette and Dyck 2007; Fahrig 2007). Therefore, evaluating metrics that correspond to the distribution and size of specific LULC classes is important for studies that incorporate the effects of habitat heterogeneity on fauna.

When studying landscape level drivers of animal space use and movement, particularly in more heterogeneous systems, matching the temporal scales of the landscape predictors to the animal space-use data is most informative to understand variations in resource use and behavior. For example, when using telemetry data of animals, we suggest first identifying the temporal scales of variations in animal movement or resource use patterns (e.g., using a change point analysis on movement data, Gurarie et al. 2009) and then correspondingly matching the temporal scale for the landscape structure. While this may not always be possible, as conducting analyses over such fine temporal scales would substantially increase the computation power and time required, it would be good to conduct the analysis suggested in this paper, and evaluate multiple temporal scales to understand how changes are occurring within the landscape. Though the use of metrics often makes quantifying landscape structure easier, selecting the appropriate metrics is often more nuanced (Neel et al. 2004). Our results showed that the proportion and occurrence of change-points varied with the metric selected and the LULC class. Thus, ecological studies using data on landscape structure may also need to account for the differences between LULC classes and accordingly select a few metrics to be examined (Cushman et al. 2008). Finally, we used the visible spectra from Sentinel 2 to obtain detailed LULC classification, but synthetic aperture radar data can also be combined with visible imagery for the same purpose (Lopes et al. 2020; Samrat et al. 2021). The methodological approach we provide in our study (Fig. 1) can be used as a generic approach, and the parameters under each sub-section would need to be customized based on the study objectives and characteristics (Neel et al. 2004). However, we expect that changes in landscape structure in more homogenous landscapes will occur at relatively broader temporal scales for the dominant LULC classes.

In conclusion, when studying ecological processes, irrespective of the landscape, the appropriate temporal scales depend on the specific objectives of the study, species, and type of movement (e.g., migratory vs. non-migratory) (van Beest et al. 2011). While some habitat types experience high spatio-temporal variations in productivity and patch configurations, other landcover types remain relatively homogenous over time. Thus, identifying the scales of change in landscape structure is important for the management of landscapes and biodiversity, as characterization of a landscape's patch dynamics can provide information on the organization and stability of landscape composition and configuration (Olsen et al. 2005).

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**Author contributions** All authors contributed to the study conceptualization and design. Data collection and analysis were performed by AK. The first draft of the manuscript was written by AK and all authors commented on and revised the previous versions of the manuscript. All authors have read and approved the final manuscript.

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**Data availability** The R codes and images used for this study are available on reasonable request from the corresponding authors.

**Declarations**

**Competing interest** The authors declare no competing interests.

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