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Position Paper

LDTtool: A toolbox to assess landscape dynamics

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ABSTRACT

The “LDTtool” python toolbox is introduced. This ArcGIS toolbox can be applied to assess land cover or land use changes between two or three moments, considering landscape composition and configuration. The development of LDTtool occurs in a time when the studies on landscape dynamics looking at amount and configuration changes are becoming mainstream. The use of analytical units, whether regular polygons like squares or irregular like districts, allows to study at broad as well as at detailed scales, depending on the base maps spatial resolution and intrinsic quality. The ultimate goal of the toolbox is to assign each analytical unit to a type of dynamic. The paper shows how to operate the toolbox and provides a case study regarding the olive groves dynamics in Portugal in the period 1990–2018.

1. Introduction

Significant and/or quick landscape changes often disrupts ecosystem functioning interfering with ecological processes and thus jeopardizing their capacity to provide vital services for population (Millennium Ecosystem Assessment, 2005). Substantial landscape changes have such impact on biodiversity that habitat loss and fragmentation are often pointed as one of the major causes of biodiversity loss (Jaeger et al., 2011) in some regions and therefore regarded as a central issue in conservation biology (Saunders et al., 1991; Wiens, 1996). Since landscape patterns influence ecological processes (pattern-process relationship; McGarigal et al., 2012; Turner, 1990), landscape metrics became popular among the landscape ecologists.

To interpret landscapes as discrete patches of different land cover classes (Forman, 1995), there are two main types of changes to consider: composition and configuration changes. The former relates to what constitutes the landscape and its amounts (e.g. land cover types and how much) – *What exists in the landscape*. The latter has to do with the shape and location of the elements – *How it is distributed*. Although both types of changes co-occur, interact and even depend on each other (Lindenmayer and Fischer, 2007), the separation of their independent effects is necessary to better understand the impacts. Looking at a single measure of change without separating the contribution of the composition and configuration make studies difficult and sometimes impossible to compare (Fahrig, 2017, 2003). An increasing number of studies has been considering the importance of distinguishing the different effects of amount and geometric changes in landscape analysis (e.g. Johnstone et al., 2014; Plećaš et al., 2014; Sauder and Rachlow, 2014; Steckel et al., 2014).

Many metrics, methods and software with distinct specificities have been developed to measure landscape characteristics. Some examples of well-known software are FRAGSTATS (McGarigal et al., 2012), Conefor Sensinode 2.2 (Saura and Torné, 2009), Patch Analyst (Rempel et al., 2012), Circuitscape (McRae et al., 2013), Graphab (Foltête et al., 2012)

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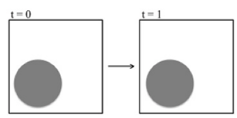
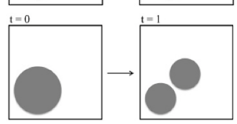
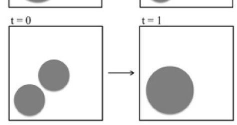
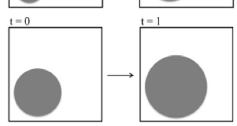
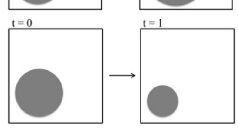
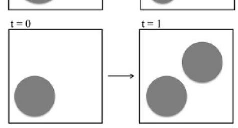
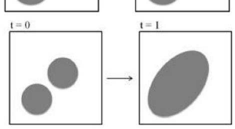
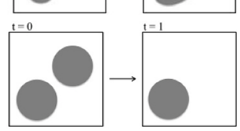
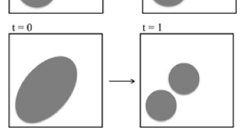
and Land-metrics DIY (Zaragozí et al., 2012). Overall, landscape study does not seem to lack tools but new ones keep being developed in order to improve the existing analytical capabilities (e.g. landscapemetrics by Hesselbarth et al. (2019); gDefrag by Mestre et al. (2019) For a broader notion of the quantity and variety of landscape analytical software existent, especially free and open source, we recommend the works by Steiniger and Hay (2009) and Steiniger and Hunter (2013).

The focus on accounting for both amount and geometric changes is the foundation of the Landscape Dynamic Typology (LDT) method (Machado et al., 2018). LDT is a set of "Types of Dynamics" (ToD) that can occur in a binary landscape, obtained via combination of two metrics that can increase, decrease or remain the same in a period between two dates: *Area* to represent composition and *Number of Patches (NP)* to assess configuration (Table 1).

LDT application can be straightforward but it can also require a heavy workload and for that reason, the transition of the original protocol to a software piece is regarded as essential to increase its adoption (Machado et al., 2018). In this paper we introduce the "LDTtool", an ArcGIS (www.esri.com) toolbox designed to facilitate and automate the application of the LDT method. We provide a comprehensive description of the toolbox as well as an illustrative case study concerning the olive grove dynamics that have been occurring in southern Portugal.

Table 1
Landscape dynamic types (adapted from Machado et al., 2018).

Type	If	and	Designation	Graphic Representation
A	$\Delta A = 0$	$\Delta NP = 0$	No change	
B	$\Delta A = 0$	$\Delta NP > 0$	Fragmentation *per se*	
C	$\Delta A = 0$	$\Delta NP < 0$	Aggregation *per se*	
D	$\Delta A > 0$	$\Delta NP = 0$	Gain	
E	$\Delta A < 0$	$\Delta NP = 0$	Loss	
F	$\Delta A > 0$	$\Delta NP > 0$	NP increment by gain	
G	$\Delta A > 0$	$\Delta NP < 0$	Aggregation by gain (NP decrement by gain)	
H	$\Delta A < 0$	$\Delta NP < 0$	NP decrement by loss	
I	$\Delta A < 0$	$\Delta NP > 0$	Fragmentation by loss (NP increment by loss)	

(A) If there is no change in an area or in the number of patches (NP) we assume that landscape (or the analytical unit extent) did not change; (B) If the area remained the same but the NP increased, it means a fragmentation occurred; (C) If the area remained the same but NP decreased, then an aggregation took place; (D) If the area increased and the NP is equal, it represents a gain of area; (E) If the area decreased and the NP did not change, there is a loss of area; (F) If both area and NP increased, it led to new patch creation; (G) If the area increased and NP decreased, an aggregation occurred due to area gain; (H) If both area and NP decreased, a patch decrement occurred due to area loss; (I) If area decreased and the NP increased, it means that fragmentation occurred due to area loss.

2. LDTtool

The LDTtool is a python-based add-on ArcGIS toolbox operational in ArcCatalog and ArcMap as well as in ArcGIS Pro. It was developed using the 10.6 version and updates to future versions will be assured in order to keep the toolbox useable.

It comprises five tools (Fig. 1). The first four tools (Landscape Dynamic Types) run the core LDT steps to calculate the dynamics occurred in the landscape. The 1.1 (2 M (Squares)) uses two moments of analysis and regular squares as analytical units. The 1.2. (3 M (Squares)), uses three moments of analysis and squares. The 1.3. (2 M (Districts) uses two moments of analysis and districts as analytical units. The 1.4 (3 M (Districts)) uses three moments of analysis and districts.

Finally, the "2 – Forecast" calculates a hypothetical scenario assuming the ongoing trends will persist. The forecast tool considers how the types of dynamics can evolve from one to the other. For instance, in the presence of area gain, the ToD G (aggregation by gain) will continue eventually until it reaches a 'total cover' situation. In the opposite direction, in a situation of area loss, the ToD H (NP decrement by loss) is going to a 'no cover' scenario when the last patch disappears. For more detailed explanation see Machado et al. (2018).

LDT works with binary landscapes and thus landscape Feature Classes must contain only one class with the polygons, that represent patches, under study (the habitat, the land cover category, etc.).

Relevant recommendations to avoid possible errors or malfunctioning are: (i) using the same coordinate system in the data frame and all the input elements; (ii) using feature classes (requires a geodatabase) instead of shapefiles and (iii) delete unnecessary attribute fields.

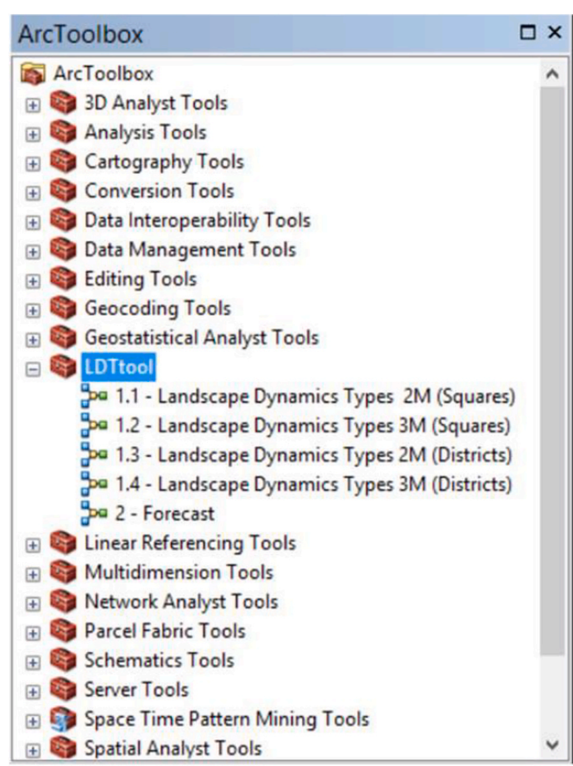


Fig. 1. LDTtool structure in ArcToolbox.

The input's quality also affects the overall quality of the analysis. For that reason, spatial and temporal resolution should be adequate to assess the phenomena under study and therefore reproduce accurately the landscape evolution.

2.1. Preliminary steps

The following preliminary steps are essential to ensure the toolbox correct functioning.

1. Create a File Geodatabase.
2. Make it the default Geodatabase (while creating it or after in: *Menu File, Map Document Properties, Default Geodatabase* (select).
3. Import the feature classes into the Geodatabase. The feature classes should be the landscape moment 1, landscape moment 2 and landscape moment 3 (optional). Regarding the analytical units, the feature classes are the study area boundary (for squares) or districts.
4. Add the "LDTtool" toolbox to ArcToolbox.
5. Select the Geodatabase as "Current workspace" and "Scratch workspace in *Geoprocessing menu, Environments, Workspace* (select).
6. Select the Geodatabase as "Current workspace" and "Scratch workspace" in the Arctoolbox *Environments; Workspace.* (select).
7. Confirm the paths are correct within each tool by Right-clicking; *Properties*; *Environments*; check the *Workspace* box*, Values* button.

2.2. Inputs and settings

The inputs and settings required to run the tools are the following: Tool 1 – Landscape Dynamics Types.

- *Study Area Polygon*: Polygonal feature class containing the study area boundaries.
- *Districts:* Polygonal feature class containing the districts boundaries.
- *Landscape Moment 1*: Polygonal feature class of the landscape in moment 1.
- *Landscape Moment 2*: Polygonal feature class of the landscape in moment 2.
- *Landscape Moment 3*: Polygonal feature class of the landscape in moment 3.
- *Squares width and height (meters):* Analytic square size.
- *Keep patches equal or larger than (square meters)*: Minimum patch size to be analysed.
- *Output Feature Class*: Name and path of the output file.

Tool 2 - Forecast.

- *Landscape to forecast (Output of tool 1)*

3. The LDTtool demonstration

In order to demonstrate the LDTtool implementation and outputs, we use the tool 1.1 and therefore there are two moments of analysis and squares are used as analytical units. We present an illustrative example of the olive grove dynamics occurred in Portugal between 1990 and 2018.

3.1. Background

Traditional olive groves are a characteristic element of Mediterranean landscapes. Besides its historical and cultural value, traditional groves often host many species making them relevant in terms of biodiversity. In Portugal, the quest for olives and olive oil self-sufficiency first, and exports increments after, led to a landscape change in the last years. New high-yielding intensive (and super-intensive) groves are fast expanding, often replacing biodiversity-rich but low-yielding traditional ones (Morgado et al., 2020). Not only traditional olive groves but also other land uses such as "non-irrigated arable land" and "permanently irrigated land", have been transformed in large-scale plantations, often with high levels of intensification.

In time, populations began to complain about several problems regarding agrochemicals among other issues. Regarding biodiversity, besides the initial land-cover change that represents a severe habitat loss for many species, it has recently been revealed that the mechanical olives harvesting at night leads to mass bird mortality (Silva and Mata, 2019). At the landscape scale there is a marked homogenization of the territory provoked by large-scale plantations. It is urgent to assure that modern groves, essential to achieve high yield production, minimize their negative environmental impacts while simultaneously the traditional groves are promoted. This might be achieved through both political and/or market mechanisms. For instance, Moreira et al. (2019) suggested new labels should be created to provide consumers with details about the grove from which the product was sourced.

3.2. Preliminary steps

A File Geodatabase was built using ArcCatalog and the feature classes were imported into it (see 2.2 Inputs and Settings subsection). Next, a blank ArcMap project was created and both the default geodatabase and the scratch workspace were pointed to the built geodatabase. Then the "LDTtool" toolbox was added to the ArcToolbox and the feature classes were loaded into the project.

3.3. Inputs and settings

We used the continental Portuguese Administrative Boundaries Official Map (2018 version) as study area and the Olive Groves of 1990 and 2018 extracted from the CORINE Land Cover maps. The analytical square size was defined as 10 km and the minimum size patch (to discard meaningless polygons resulting from intersect operations) as 50,000 m^2. It is important the chosen dimensions are appropriated relative to both the base maps and the phenomena under study. Since CLC uses a minimum size patch of 25 ha (250000 m^2), selecting smaller minimum size patches does not to improve the spatial resolution. Also, we knew beforehand the landscape changes in Portugal involving groves are mostly due to large scale plantations, often larger than 50,000 m^2.

The output feature class was named "LDT_OliveGroves" (Fig. 2a). This feature class was then used as input for "Tool 2 – Forecast" (Fig. 2b).

3.3.1. Square size selection

The tool allows the use of districts and squares as analytical units. Although the pros and cons are common to both types of analytical units (see subsection "3.5. Results and discussion" for more on the Modifiable Areal Unit Problem - MAUP), the districts are usually used for some specific reason and often exempted from further justification while the artificial sampling schemes such as regular grids tend to be more scrutinized. For example, a county boundary is as artificial for some natural processes as a square or an hexagon but it is commonly accepted that data has to be aggregated by county our any other administrative or statistical unit. In analytical terms the repercussions may be similar but when using an artificial sampling grid an extra attention is required to make sure the sampling scheme itself is not adulterating the raw data. Since there is not a single solution for this problem and there are a multitude of contexts and applications, users often have to find a way to assess quality and establish tolerance levels. Regular areas like squares can be used for no particular reason but many times are used because there are many associated data available in that format, thus allowing variable extraction for posterior analysis. One important aspect to consider is how well the sampling scheme preserves the integrity of the base data. For instance, in our case study, a single patch can be recognized by the software as being multiple patches because it crosses several squares (or districts). Since the final calculations are based on the analytical unit and not on the patches themselves, the same patch

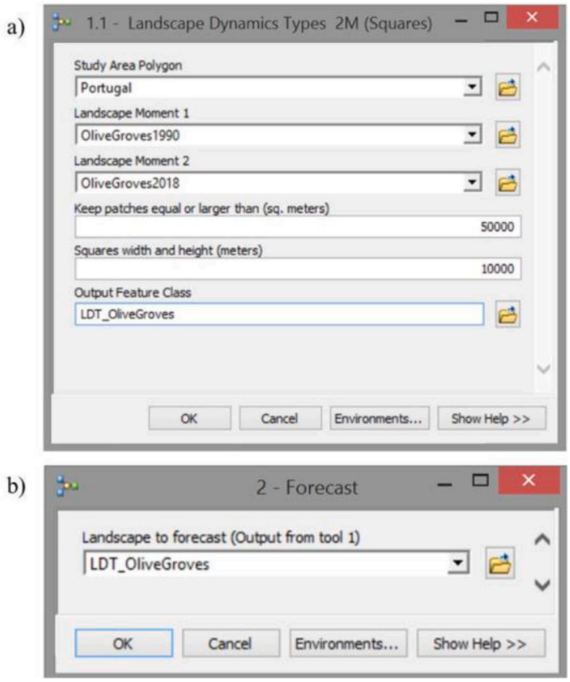


Fig. 2. Filled dialog boxes. a) Tool 1.1 - Landscape dynamics Types 2 M (Squares); b) Tool 2 - Forecast.

can be counted multiple times. Ultimately, the only way to solve this problem was to use the study area boundaries and discard the use of analytical units. The downside of such an option is the complete loss of spatial resolution and its associated benefits. In our view, a good compromise would be a grid size that minimizes patch intersection and still offers an adequate spatial resolution to assess the phenomenon being studied. To what NP are concerned, olive groves maps show 1613 patches in 1990 and 1974 in 2018. After intersecting the grid composed by 1011 100 km^2 squares, the NP was 2220 and 2685, respectively. This represents 607 artificial extra patches for 1990 and 711 for 2018. The intersections per square were 2,2 for 1990 and 2,7 for 2018. To improve the spatial resolution requires smaller squares that would make these numbers worse. On the opposite direction, to improve these numbers we would have to enlarge the squares and lose spatial resolution.

As to patch size, the average olive grove was 1,72 km^2 in 1990 and 1,76 km^2 in 2018. Thus, a 100 km^2 square would be large enough to fit several patches and to minimize the original patches crossing several squares. Looking at the extremes of the patch size distribution, only one patch in 1990 and 2018 is larger than 100 km^2. This suggests that the grid size is not too small. It could be larger but the larger the square is, the more patches it can fit and that increases the risk of hiding some ToD by losing spatial resolution. Overall, these values seemed acceptable for the task in hands but could the output be too influenced by the square size? To answer this question we reran the tool using 9 km, 10 km, 11 km and 12 km squares that differ 10% and 20% from the original 10 km grid. This allowed us to assess the MAUP's scale effect. Having different sizes, the grids are distinct, the squares are not in the same place, and with that we were also assessing the MAUP's context or zoning effect. With the 10 kmX10km squares as a starting point, we used R software (R Core Team, 2018) to run Chi-Squared tests against all the other grid sizes, based on the ToD counts. The results show the ToD counts display no significant differences and thus are considered similar. A complementary visual analysis of the ToD spatial distribution also reveals consistency among different square sizes, albeit some expected variations. The Chi-Squared test results and the maps are provided as supplementary material.

3.4. Outputs

The final product is a feature class with the study area divided by squares, each one with the metrics calculated for both dates, their variation and assigned to a ToD (Figs. 3 and 4).

3.5. Results and discussion

The aim of this particular case study was to illustrate how to use the LDTtool and show the type of outputs it produces. The analysis was a broad one and did not intend to explain exhaustively the reality behind the olive groves increment in Portugal, which is a complex issue and would require more and different data with higher spatial resolution, possibly thematic resolution (distinguish between traditional and modern olive groves) and temporal resolution (use intermediary dates to better identify the paces in the land cover changes).

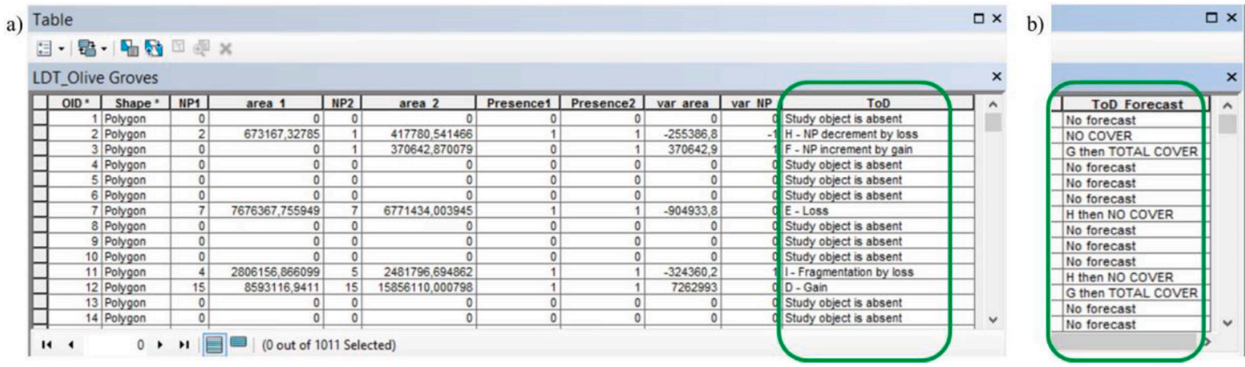
Although other drivers may be responsible for local changes occurring all over the country, it is hard to ignore the process of rapid agricultural intensification going on in the Alentejo Region (Southern Portugal) and its relevance to the landscape transformation. The traditional extensive, multi-functional agricultural systems, adapted to the Mediterranean climate are being rapidly replaced by more intensive and irrigated cultures. This was made possible due to public investment in the Alqueva dam and its integrated irrigation system, together with national and EU agricultural policies (Silveira et al., 2018). As a result, large scale intensive and super-intensive olive groves have been implemented in the last years in newly irrigated areas.

According to CLC (CHA00, CHA06, CHA12 and CHA1218) the land covers that have been replaced the most by olive groves are "non-irrigated arable land" and "permanently irrigated land", presumably land that was not irrigated before but has now access to water and land that was already irrigated but was used for other cultures. In opposition, some existing olive groves were replaced by, mostly, "non-irrigated arable land" and "transitional woodland-shrub", what can reflect the low income obtained by traditional olive groves that were abandoned.

Comparing the 1990 and 2018 feature classes we verify there have been an olive grove area increment of 692,84 km^2 and a number of patches increment of 361. These overall values suggest the "Type of Dynamic F–NP increment by gain" has been the main change pattern taking place at the study area. The results based on the 100 km^2 grid provide more detailed results. The number of squares assigned to each ToD at this spatial resolution is present in Fig. 5a).

The "ToD F–NP increment by gain" was the most represented ToD with a total of 227 squares which is in line with the global trend previously mentioned. ToD F represents new olive tree plantations not adjacent to existing ones. The magnitude of ToD F reflects how vigorous the olive grove implementation in Portugal has been. Nevertheless, there were some local area losses, presumably traditional and less profitable groves. The second most identified ToD was the "H–NP decrement by loss", present in 101 squares. It shows squares where the main dynamic was the shift from olive groves into other land covers. Looking at the number of squares it seems quite significant with almost half of the ToD F (101 vs 227). However, the relation does not stand when we compare olive grove area variation as ToD F involved an area gain of 817,57 km^2 while ToD H involved an area loss of 159,61 km^2 (Fig. 5b).

The other two ToD with variation in both configuration and composition are "G – Aggregation by gain" that reflects situations where new plantations or expansion of existing ones originated the fusion of patches (groves), and "I – Fragmentation by loss", where the loss of area provoked the division of patches. ToD G was identified in only 16 squares but totalled an area gain of 143,82 km^2, while ToD I was identified in 55 squares and implied an area loss of 118,05 km^2. Focusing on the ToDs that reflected only composition and had no influence in the NP, "D – Gain" was found in 49 squares and involved an area gain of 57,18 km^2, while "E – Loss" occurred in 71 squares with a



a) Table

LDT_Olive Groves

OID *	Shape *	NP1	area 1	NP2	area 2	Presence1	Presence2	var area	var NP	ToD
1	Polygon	0	0	0	0	0	0	0	0	Study object is absent
2	Polygon	2	673167,32785	1	417780,541466	1	1	-255386,8	-1	H - NP decrement by loss
3	Polygon	0	0	1	370642,870079	0	1	370642,9	1	F - NP increment by gain
4	Polygon	0	0	0	0	0	0	0	0	Study object is absent
5	Polygon	0	0	0	0	0	0	0	0	Study object is absent
6	Polygon	0	0	0	0	0	0	0	0	Study object is absent
7	Polygon	7	7676367,755949	7	6771434,003945	1	1	-904933,8	0	E - Loss
8	Polygon	0	0	0	0	0	0	0	0	Study object is absent
9	Polygon	0	0	0	0	0	0	0	0	Study object is absent
10	Polygon	0	0	0	0	0	0	0	0	Study object is absent
11	Polygon	4	2806156,866099	5	2481796,694862	1	1	-324360,2	1	I - Fragmentation by loss
12	Polygon	15	8593116,9411	15	15856110,000798	1	1	7262993	0	D - Gain
13	Polygon	0	0	0	0	0	0	0	0	Study object is absent
14	Polygon	0	0	0	0	0	0	0	0	Study object is absent

(0 out of 1011 Selected)

b)

ToD Forecast
No forecast
NO COVER
G then TOTAL COVER
No forecast
No forecast
No forecast
H then NO COVER
No forecast
No forecast
No forecast
H then NO COVER
G then TOTAL COVER
No forecast
No forecast

Fig. 3. Output attribute table. a) Output of Tool 1.1 - Landscape dynamics Types 2 M (Squares); b) Field originated by Tool 2 – Forecast.

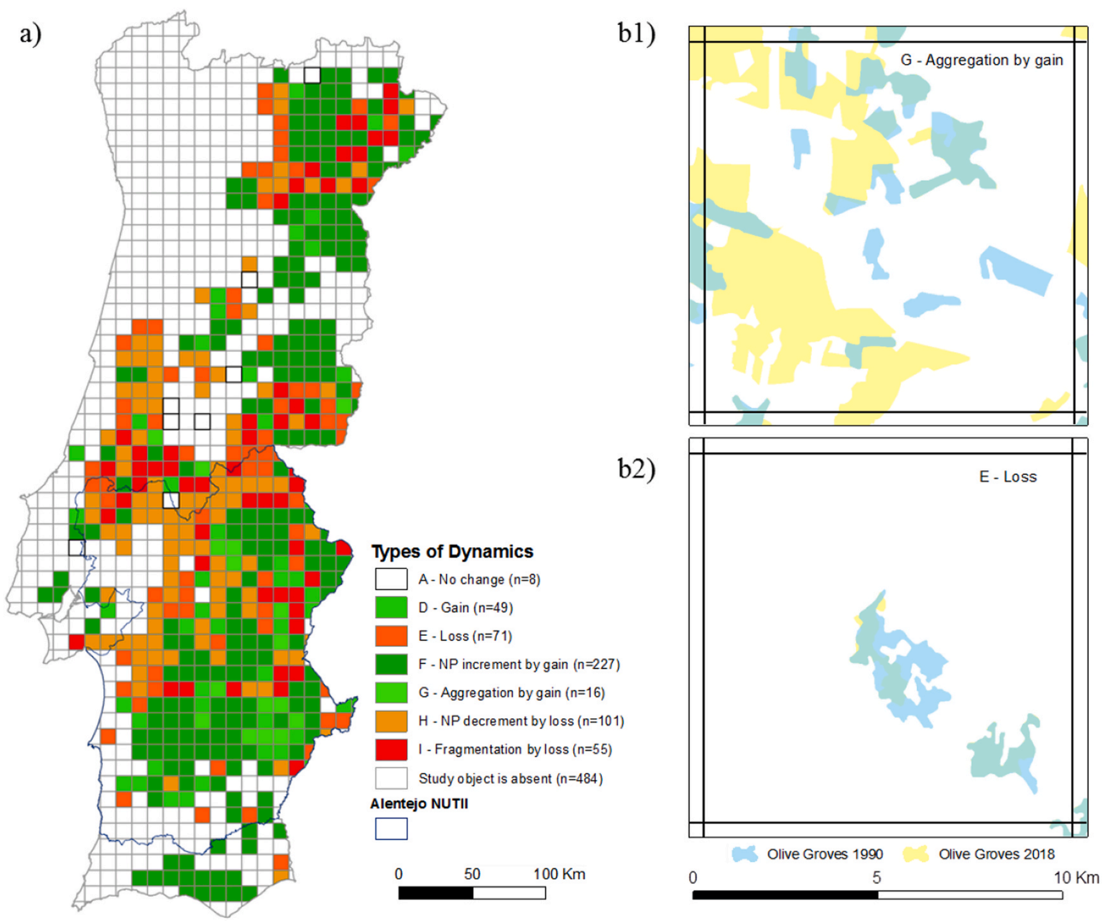


Fig. 4. Olive Groves in Portugal (1990–2018). a) Map produced by "Tool 1 - Landscape Dynamics Types 2 M (Squares)" showing Continental Portugal divided by 10 × 10 Km squares with assigned Types of Dynamics (ToD). b1) Detailed view of a square showing TOD G - Aggregation by gain. b2) Detailed view of a square showing ToD E – Loss.

total loss of 47,83 km^2. No squares were assigned to the ToD B or C, that represent pure geometric changes (without amount variation) and thus do not occur often.

In summary, there were many changes in olive groves in Portugal between 1990 and 2018. Overall, the area increased despite some local losses. Most of the amount changes had implications on the olive groves configuration (shape and spatial distribution). In a situation (or scenario) of olive groves substantial area increment, all the ToD related to area gain may contribute to landscape homogenization. Obviously, the area amount turned into olive groves is the main thing responsible for that contribution but considering a fixed amount, the way it is added to the landscape is also relevant. While pure gain, meaning the existing patches were expanded (ToD D – Gain), and the presence of new patches (ToD F–NP increment by gain) have influence mainly at the landscape granularity level, the fusion of patches (ToD G – Aggregation by gain) contributes directly to the landscape spatial homogenization. Also related to this, particularly if considering biodiversity issues, it is fundamental to verify the starting point of each square as a given amount of area change may have different meanings and effects. In other words, similar areal increments may have different impacts if the square had none of that cover, or if the square already had much of it. The LDT forecast tool should be used with caution as its purpose is to support the

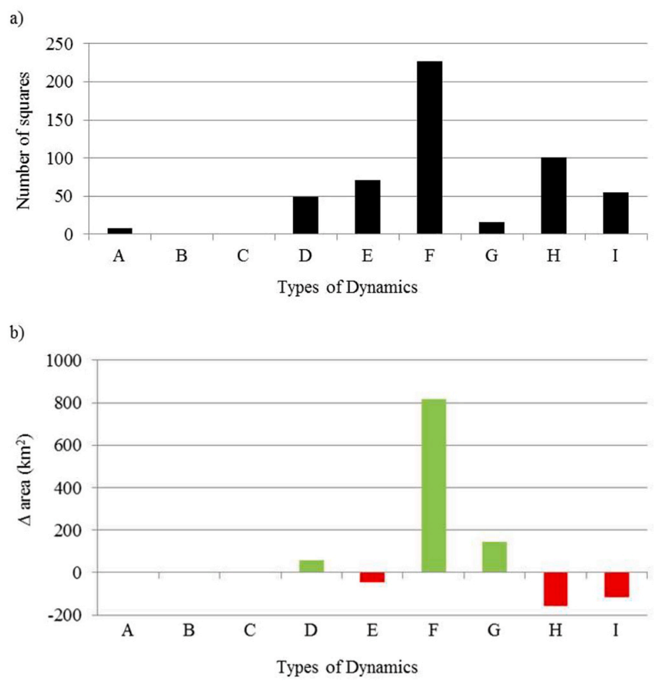


Fig. 5. a) Number of squares assigned to each Type of Dynamics; b) Olive grove area variation associated to each Type of Dynamics.

thinking process of how the landscape may look like in the future and not to make accurate predictions. Based on the LDT forecast model, we can see that if there is an increasing trend, in time, the existing patches of a given land cover may expand so that they bridge the gaps between them and merge together (ToD D evolves to ToD G). New patches that are installed in the landscape may follow the same path (ToD F is followed by ToD D which evolves to ToD G). Such analysis act as a diagnosis and projects a hypothetical future based on the current trend. Nevertheless, we must advise this tool is better suited for situations where natural processes are in place without management or with little human interference (e.g. vegetation recovery, afforestation, etc.). In some cases it could be useful to study different forms of ownership, for instance large landowners who manage intensively and a multitude of small owners who have no interest in management and this consequently leads to abandonment of agricultural use. In the case of planned, highly managed olive groves (or any other agricultural land) the land use changes are mostly dependent of human decision. For instance, the tool shows us the ToD F and ToD D may end up originating a higher number of ToD G squares, which implies a greater spatial homogeneity than we have today. This may end up being true but it is hard to sustain this prediction because the olive groves will not expand naturally via dispersal. Instead they will appear and disappear due to human direct intervention in the territory.

The analytical grid allowed us to identify local dynamics along the study area and visualize them in a map (Fig. 4a). This enhanced capability can be relevant for planning, management and decision making processes. Although there are valuable advantages provided by the use of analytical units, we must highlight the modifiable areal unit problem (MAUP) (Gehlke and Biehl, 1934; Openshaw and Taylor, 1979). The MAUP refers to the fact that the areal units can be set arbitrarily and are modifiable. Results based on aggregated data following areal units can change if the same data are aggregated under different areal units (Waller and Gotway, 2004). Commonly used in population-focused studies, data aggregation is often based on boundaries such as zip codes, census tracts and census block groups (Moon and Farmer, 2001). Regular grids are extensively applied in spatial analysis to avoid bias caused by administrative divisions (Swift et al., 2008) and/or to include the vast amount of data that is available in that format, such as remote sensing data, biological atlas or simply because there is a preference for working with squares (e.g. UTM) or hexagons as a reference.

MAUP is a long standing issue in geography and spatial analysis that has no optimal solution and has been ameliorated by the researchers according to their study contexts. Among several attempts that were made to deal with the MAUP (Openshaw, 1984), proposed that areal units should match the optimal spatial variance or maximize a given statistic. This is a clear protocol that leaves no doubt as to how the units are designed, but at the same time it is easy to criticize as it allows researchers to design spatial units in order to achieve a preferred result. According to Swift et al. (2008), areal units generated from Voronoi tessellations (Thiessen polygons) can be effective to reduce aggregation bias. The same authors point out that sensitivity analysis can be superior to other methods (e.g. optimizing the size and shape of areal units) since it does not rely on highly accurate measurements of spatial variables. Long et al. (2010) highlighted that MAUP influences the results, and suggested a multiscale approach when implementing their metric 'proportion of landscape displacement from configuration' (Py) as a way to minimize scale-related bias. Butkiewicz et al. (2008) first introduced a geospatial visualization method and later provided a number of enhancements to help lighten the effects of the MAUP (Butkiewicz et al., 2010).

In our example, if the squares had a different size (scale effect) and/or a different location (context effect), their content in terms of olive groves would also be different. Scale effect assessment would require testing different square sizes and context effect assessment would require changing their location. Although the current LDTtool version does not include such validation instruments, similar operations can be conducted by running the tool using different size grids (scale effect) and feeding the tool with edited grids (rotation, translation, etc.) via tool 1.3. or 1.4. (context effect). We took a similar approach and added a statistical test to assess the outputs (see Supplementary Material). A future validation/quality control procedure to integrate LDTtool is likely to involve an automatization of such steps and will be incorporated in the existing tools or provided as separated analytical tools.

4. Concluding remarks

The newly developed LDTtool can add value to studies in a wide range of topics related to biodiversity conservation, invasive species, ecosystem services and natural resources planning, mainly if land use, land cover or habitat changes are a central topic of the study. After the toolbox functionalities were presented, a demonstration was provided using as an example the olive groves dynamics in Portugal in the period between 1990 and 2018.

4.1. Strengths, limitations and future developments

The LDTtool's strengths and limitations are twofold: those intrinsic to LDT and those related to the software itself. Some of the LDT method's virtues are its simplicity due to the fact of being based on simple spatial metrics and the easy interpretation of the outputs that come in the form of value variations and maps (Machado et al., 2018). LDTtool itself, being introduced as an ArcGIS toolbox is expected to be user-friendly. The toolbox configuration is straightforward and it runs smoothly and fast mostly because it uses the vectorial format. LDTtool is implemented/coded in Python, which is a versatile language widely used in geoprocessing. Additionally the source-code is available and users can extract it and edit it to fit their purposes. The possibility to adjust parameters such as the minimum patch size and the analytical units also add versatility to the process. However, the use of analytical units (regular polygons such as squares or irregular polygons such as districts) does not come without a cost, which in this case is related to MAUP. Variations in how regions are delineated have an influence in how the data is aggregated. Scale has similar implications because local variation can be lost when aggregated into a larger region (e.g. 20 Km squares instead of 10 Km squares). Therefore, both scale and analytical units must be cautiously selected in order to fit the purpose of the study. Although this is up to the user, we are aware that an automated validation procedure that helps mitigate the MAUP implications would highly improve LDTtool.

Also the use of binary landscapes facilitates the analysis but can be too simplistic to represent reality, mainly in biodiversity studies, particularly those involving habitat suitability or functional connectivity.

The current version is not a final product but rather the first version of a tool that has room to improve and will be updated to assure its usability. LDTtool's current limitations are identified and will be the base for future developments. Some upcoming improvements being considered at the moment are (i) quality (sensibility or robustness) analysis of the final results to minimize the MAUP limitations, (ii) expand the analytical possibilities beyond binary landscapes, and (iii) integration in other GIS platforms.

Software availability

Name: LDTtool.

Availability and cost: LDTtool can be can be freely downloaded from: https://github.com/RDPMachado/LDTtool.

(Includes a README file with description and instructions).

License: GNU GPLv3; Developer: Rui Machado; Contact address: Departamento de Paisagem, Ambiente e Ordenamento, Universidade de Évora, Rua Romão Ramalho, n◦ 59, 7000-671 Évora, Portugal, E-mail: rdpm@uevora.pt.

Year first available: 2020.

Software required: ESRI® ArcMap™ 10.0 and later versions.

Program language: Python.

Program size: 6.97 Mb.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2020.104847.

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