A NEW METHODOLOGY TO QUANTIFY STRUCTURAL LANDSCAPE IMPACTS OF LAND USE/LANDCOVER CHANGE USING MOVING WINDOW METRICS. A CASE STUDY IN A CHILEAN COASTAL BASIN

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Abstract

Land use and land cover changes (LULC) result in alterations to landscape structure, with particularly significant consequences in the landscapes of coastal basins due to their unique characteristics and special sensitivity. The aim of this work was to introduce a new methodology to assess the impacts of LULC transitions on landscape structure in a coastal basin of the Los Ríos Region in Chile. Changes in landscape patterns were assessed by analysing systematic transitions in conjunction with moving windows landscape metrics and spatial cluster analysis. An index measuring the impact of transitions on landscape structure change (ITSC) was calculated to assess the degree to which each systematic transition contributed to the spatial cluster of landscape change. The proposed method showed that transitions resulting from the replacement of native forest and especially those which involve its transformation into forestry plantations, have the greatest potential impact on landscape structure in the basin. Therefore, planning and management measures must be established to prevent such transitions, so avoiding a massive change in landscape structure.

Keywords: Moving windows, spatial landscape metrics, LULC, systematic transitions, Land use planning, Forest plantation

Introduction.

Land Use and Land Cover Change (LULCC) are some of the leading spatial measures of global change (Grimm et al., 2008). Generally, these changes impact on complex landscapes and socio-ecological systems affecting the provision of ecosystem services and human wellbeing (García-Llamas et al., 2019; Hermann et al., 2011). For this reason, LULCC has been widely studied over the past decades, and an extensive body of literature has been produced. This focuses particularly on how LULCC affects landscape structure, including i) landscape composition (number and quantity of land use/cover classes); and ii) landscape configuration (the spatial relations between the different elements that make up the landscape) (Aguilera-Benavente et al., 2014; Botequilha-Leitão & Diáz-Varela, 2018).

As regards landscape composition, many studies have focused on quantifying LULCC transitions. In most of them, the only transitions considered relevant for further analysis are those representing an area of high landscape change (Arowolo & Deng, 2018; Peña-Cortés et al., 2021). However, relevant transitions can also be defined according to how much change has actually occurred in the transition area, as compared to the change expected according to its proportion of total LULCC in the study area as a whole (Pontius et al., 2004). To address this, the relative sizes of the LULC classes are incorporated into the analysis to define the expected change values for each transition (Bonilla-Bedoya et al., 2014; Galletti et al., 2016). The transitions showing higher or lower values of change than expected are called “systematic transitions”**.**

Research into landscape structure has generally tried to characterize changes using landscape metrics based on the patch matrix model (PMM) (Aguilera et al., 2011; Hermosilla-Palma et al., 2021; Wu et al., 2011). These metrics have been used to quantify features such as fragmentation, dispersion, shape, and heterogeneity. However, the discrete nature of the PMM and the global values of landscape metrics (class or landscape level) fail to capture the continuous spatial heterogeneity of spatial patterns at different scales (Cushman & Landguth, 2010).

A possible alternative approach involves the gradient-based model (Cushman & Landguth, 2010; Lausch et al., 2015), which uses spatial landscape metrics implemented by a moving window technique (Hagen-Zanker, 2016). The moving window allows a continuous representation of the landscape to be obtained from categorical data. This method produces an image with a single metric value for each pixel, both at class (e.g. percentage of the landscape: PLAND) and landscape level (e.g. Shannon diversity index: SHDI; heterogeneity) (Díaz-Varela et al., 2009; Diaz-Varela et al, 2016)**.** Consequently, the spatially explicit nature of these landscape metrics provides the spatial dimension needed to integrate the study of changes in landscape structure into land use planning (Lausch et al., 2015) and allows these to be combined with other methods of spatial analysis, such as map algebra, LULCC analysis, and spatial statistics.

However, little research has been done on the detection of changes in landscape structure using moving window landscape metrics. Some of the existing studies apply moving window metrics to assess patterns of urban growth using different window sizes (Wang et al., 2021); or changes in landscape structure in cities by comparing spatial metrics over time (Lv et al., 2018). Moving windows have also been applied to characterize spatial patterns for land use and transportation planning (Soria-Lara et al., 2016), and to assess the degree to which landscape structure can determine habitat suitability and resistance patterns for species in rural landscapes (Ducci et al., 2015). Another area of application of spatial metrics is the identification of homogeneous areas by analyzing landscape structure at different scales (Botequilha-Leitão & Diaz-Varela, 2018) or by heterogeneity assessment (Diaz-Varela et al, 2016). However, none of these studies have integrated land use transitions analysis with moving windows techniques to spatially assess changes in landscape structure. A method with these characteristics could provide insights to help identify the transitions with the greatest impact in terms of the changes they make to landscape structure. The identification of those transitions would be a valuable information for spatial planning, especially in South America where massive changes in landscape structure have occurred throughout the continent (Song et al., 2018).

In this regard, Chile is a good example of such changes, with huge transformations in the landscape due to the expansion of forest plantations, agriculture, and urban areas (Miranda et al., 2017). Even though these land uses may have contributed to economic growth (Lebdioui, 2019), they have also had a number of negative environmental and social impacts, such as impairing the quality of water supply (Lara et al., 2009) and habitats (Hermosilla-Palma et al., 2021). In these cases, spatially explicit landscape metrics can be used together with systematic transitions to identify those LULC transitions with the greatest impact on landscape structure (diversity, heterogeneity, etc). This could be even more important in the coastal basins of the regions of La Araucanía and Los Ríos (Chile) where the expansion in forest plantation in recent decades has produced massive LULCC (Miranda et al., 2017; Peña-Cortés et al., 2006, 2021).

Within this framework, this paper proposes a new methodology to assess which LULC transitions make the greatest contributions to landscape structure change. This research question was complemented with the following objectives:

i) To analyse LULCC dynamics in the coastal basin of the Lingue River (Los Ríos Region, Chile), over the period 1987-2009, so as to detect systematic transitions.
ii) To characterize changes in landscape structure using spatial landscape metrics (through moving windows) and map changes considering four dimensions of landscape structure (diversity, naturality, contrast and juxtaposition).
iii) To quantify the contribution made by each systematic transition to changes in landscape structure, identifying whether that contribution was greater than expected according to its percentage share of all the LULCC in the study area.
iv) To take the results of the analysis into account as regards their implications for future regional plans in Southern Chile.

2. Materials and methods.

2.1. Study area.

The study area encompasses the Lingue River Basin, located in the coastal zone of the Los Ríos Region, between 39° 00' and 39° 30' South, and 72° 45' and 73° 30' West (Figure 1). The Lingue River Basin has an area of 69,144 ha and for administrative purposes is part of the county of Mariquina. The basin is characterized by landforms such as mountain ranges, marine erosion platforms and extensive fluvial-marine plains. According to Di Castri & Hajek (1976), the climate is predominantly oceanic with Mediterranean influence, and has an average annual precipitation of between 1200 mm and 1600 mm. During the colonial period, and especially since the late 19th century, the native forest has been extensively deforested, due to timber extraction, land clearance for agriculture, and livestock farming (Peña-Cortés et al., 2020). At the start of the 20th century, extraction of native timber and expansion of agriculture were the main change factors (Peña-Cortés et al., 2020). However, since the late 1970s, state-based subsidies for afforestation, largely with exotic species (*Eucalyptus spp., and Pinus spp.*), have led to substantial changes in the landscape in central and south-central regions of Chile (Miranda et al., 2017), an area that is particularly vulnerable to changes of this kind due to the lack of any specific land use management plan or any protected areas.

2.2. Land use/cover data.

The Land Use / Land Cover (LULC) maps of the Lingue river basin were generated by supervised classification of two LANDSAT 5 images using TerrSet software, path 233, row 087, for the years 1987 and 2009, downloaded from the United States Geological Survey (USGS). Images free of clouds were selected for the summer. The initial image selected (LANDSAT 5 TM 233/087 February 1987) was the oldest image available from a TM sensor for the study area. The final image was selected for 2009 (LANDSAT 5 TM 233/76 February 2009). The resulting 22-year period was that of greatest expansion of exotic forest plantation ever reported in the country (Miranda et al., 2017). Atmospheric effects were corrected on both images using the dark pixel method (Chavez, 1996). The training and validation sites were identified through high-resolution aerial images (SAF; 1m resolution, and SPOT 6; 6m resolution), data from the official Chilean Cadastral of Vegetation Resources (1997, 2007) and Google Earth. Classifications were generated using the maximum likelihood algorithm obtaining eleven classes: Old-growth Native Forest (Og-NF), Second-growth Native Forest (Sg-NF), Shrubland (Sland), Exotic Forest Plantation (EFP), Young/Harvested Exotic Forest Plantation (YH-EFP), Grassland (Gland), Agricultural land (Aland), Wetlands (Wet), Beaches and Dunes (B&D), Water (Wat), and Urban areas (Urb). Finally, LULC maps were validated using an error matrix (see supplementary material), so obtaining an overall accuracy of over 85% (Foody, 2008). Figure 1 shows the results of the classification process.

[insert figure1]

2.3. Methodology.

The aim of this study was to determine the contribution made by LULC transitions to changes in the landscape structure (Figure 2) by proposing a new methodology that measures the contribution of each LULC transition to structural landscape change through a new index measuring the impact of transition on landscape structure change (ITSC index). To achieve this objective, our methodology applies the procedure for analysing systematic LULC transitions proposed by Pontius et al (2004); spatially explicit measures of landscape structure through moving window spatial metrics (Frazier & Kedron, 2017) and spatial cluster analysis (Anselin et al., 2021). The methodology can be divided into four main steps: a) Analysis of LULCC in the study area, including the identification of systematic transitions (Pontius et al., 2004) b) Analysis of the landscape structure using spatial landscape metrics c) Assessment of changes in the landscape structure; d) Evaluation of the relationship between systematic LULC transitions and changes in the landscape structure by measuring the impact of these transitions on landscape structure change (ITSC index) (see section 2.3.5).

[insert figure 2]

2.3.1. *Analysis of land use and land cover changes between 1987 and 2009.*

The quantity and location of LULCC was obtained by cross-tabulation of the classifications for 1987 and 2009, using the crosstab function in the Terrset software (Figure 2A). From the change matrix, the systematic LULC transitions were identified according to the method suggested by Pontius et al. (2004). This method states that transitions can be branded as "systematic" when gains and losses of LULC categories are higher than would be expected in line with its percentage share of total LULCC in the study area. To identify systematic transitions in this way, the first stage is to determine the reference gains and losses for LULC. The difference between the real change and the expected change, divided by the expected change will then give us a ratio analogous to the ratios that form the basis of chi-square tests (equation 1):

$$\frac{Real\ change - Expected\ change\ in\ a\ random\ process}{Expected\ change\ in\ a\ random\ proccess} \qquad (1)$$

According to Pontius et al. (2004), the transitions in which the ratio > 0 can be defined as systematic, meaning that they occur due to the selective replacement of some pre-existing LULC. Finally, an image was generated showing all the systematic transitions (see Figure 2 A).

2.3.2. Landscape pattern analysis through moving window landscape metrics.

The analysis of landscape structure was based on the selection of some of the seven universal landscape structure components proposed by Cushman (Cushman et al., 2008). Of these seven components, we chose three, i.e. contagion/diversity, edge contrast and interspersion (mixture), so as to represent spatial processes of importance for spatial planning, such as landscape homogenization (Aguilera et al., 2011; Botequilha Leitão & Ahern, 2002). One single metric was chosen to represent each of these components (Aguilera-Benavente et al., 2014; Cushman et al., 2008) from a large set of highly correlated metrics to quantify each landscape component (Aguilera-Benavente et al., 2014; Cushman et al., 2008). As a result, three well-known, commonly used landscape metrics were selected on the basis of their simple, user-friendly interpretation: i) Shannon's Diversity Index (SHDI); ii) ECON_MN for edge contrast and iii) The IJI Index for intersection and juxtaposition (a detailed description of the metrics can be found in the supplementary material). All these metrics were calculated through moving windows and provided a spatially explicit representation of landscape structure according to the landscape gradient model (Lausch et al, 2015; Hagen-Zanker, 2016).

An additional metric measuring the naturality of the landscape was also applied. This involved a naturality index (see supplementary material) which calculates the naturality of each point of the landscape according to the surrounding LULC. To spatially represent this concept, an image was generated based on the moving windows calculation of PLAND, which represents the percentage of each LULC relative to the total landscape area. Using this method, 11 images were obtained, one for each LULC. The images were then combined through a weighted sum using the naturality value assigned to each LULC. These naturality values were defined on the basis of an assessment of the naturality of the LULC classes as described by the Chilean Forestry Agency (CONAF). This assessment was carried out by 9 academic experts using the Delphi method. The naturality values assigned to each LULC range from 0 to 1, where 0 indicates the lowest naturality value (e.g., urban areas) and 1 the highest naturality value (e.g., Old-growth Forest) (see supplementary material).

In a similar way, to estimate the ECON_MN, we assigned values of between 0 and 1 to each pair of LULC categories, according to the degree of thematic similarity between the categories (see supplementary material for the contrast matrix). In this way, a high contrast value was given to pairs of LULC categories with very different ecological characteristics (e.g., Og-NF and Urb; Wet and EFP), while low contrast values were given to pairs with similar characteristics (e.g., EFP and YH-EFP). Hence, this metric highlights areas of high naturality which are subject to high levels of anthropogenic pressure.

2.3.3. Moving window size estimation.

When using a moving window to obtain spatial landscape metrics, one important challenge is to determine the most suitable window size for the calculation, given the scale dependence of the results. According to Diaz-Varela et al. (2009), the most suitable window size can be determined by comparing the dissimilarity (S) between images of the SHDI metric for different window sizes. Dissimilarity (S) can be obtained for each window size according to equation 2.

$$Si = \frac{Mmax - Mi}{SDi} \quad (2)$$

where: *Mmax* is the mean of the metric for the biggest window size considered; *Mi* is the mean of the metric for the window size in question, and *SDi* is the standard deviation of the metric for window i.

A gradual decrease in the value of S is to be expected as window size increases. Increasing the window size when calculating the metric will therefore result in a reduction in the amount of information provided, until it reaches the point that the metric becomes independent of scale (Díaz-Varela et al., 2009**.** To find this threshold, the gradient of S (pi) needs to be calculated between each pair of window sizes using equation 3:

$$pi = \frac{\Delta Si}{\Delta Wi} - 1 \quad (3)$$

Where ΔSi is the percentage increase in S with respect to the maximum value of S, and ΔWi is the percentage increase in window size with respect to the maximum size value.

Therefore, when pi > 0 the moving window only detects local effects, which are highly scale-dependent and can therefore be identified as the local scale; however, when pi < 0, the heterogeneity of the landscape becomes independent of window size. Some authors refer to this as a “second domain” or mesoscale (Díaz-Varela et al., 2009) and propose it as the most appropriate scale for analysing landscape structure.

2.3.4. Landscape pattern change.

The changes in landscape structure for each dimension (SHDI, ECON_MN, IJI and Naturality) were obtained for the Lingue basin by calculating the difference between spatial landscape metrics using map algebra. As a result, four raster images were obtained to represent the differences between the pairs of images for each spatial landscape metric (see Figure 2B). A LISA test (Local Indicator of Spatial Association) was then performed using the GEODA software (Anselin et al., 2021) on each of the four images indicating the changes in landscape structure.

The LISA test was carried out using the *queen* contiguity weights calculation (*pvalue*=0.05 and 999 permutations). The test allowed us to identify cluster zones from values showing high spatial autocorrelation. In this way, we were able to identify highly autocorrelated zones with high or low values (++ / --) for each metric, and zones of no significance. As a result, we obtained four maps showing the areas (spatial clusters) with highly correlated values of landscape structure change (positive or negative) for each landscape metric (Figure 2C).

2.3.5. LULC transitions with the greatest impact on landscape structure change: ITSC index.

This paper aims to test whether some LULC transitions have a greater impact on landscape structure than might be expected according to their proportion of LULC change (e.g., a LULC transition which accounts for 10% of the systematic change across the landscape may account for 40% of the areas with high diversity loss, which means that the transition has a higher impact than expected on structural landscape change). To explore this question, the total number of pixels corresponding to each systematic transition inside each spatial cluster (frequency) was compared with the expected number of pixels estimated according to the percentage of the total area of systematic transitions occupied by that specific transition (reference values). To do so, we began by obtaining the number of pixels in each transition in each spatial cluster using map algebra. This was then compared with the expected number of pixels (reference values) included in each cluster according to the proportion of LULC change represented by each transition.

The reference values can be computed using expression 4, in the same way as the reference values for systematic transitions were computed in section 2.3.1:

$$Ref_{ij} = \frac{Number\ of pixels\ of\ transition\ i\ on\ cluster j \times pixels\ on\ cluster\ j}{Total\ area\ of\ systematic\ transitions} \qquad (4)$$

Finally, the real number of pixels for each systematic transition inside the spatial clusters was compared to the reference values. In this way, we obtained a measure of the impact of that transition on landscape structure change (ITSC index). This index was calculated using expression (5), in which the difference between the real number of pixels in transition *i* in cluster *j* and the reference values, is divided by the reference values. The outcome is a ratio analogous to the ratios used in chi-square tests.

$$ITSC_{ij} = \frac{Pixels\ for\ transition\ i\ on\ cluster\ j - Ref_{ij}}{Ref_{ij}} \qquad (5)$$

The index was estimated for each systematic transition within the spatial cluster of positive (C+, gain) or negative (C-, loss) change for each landscape component (diversity, edge contrast, juxtaposition and naturality).

If $ITSC_{ij} > 0$, this means that transition *i* made a significant contribution to changes in *j* landscape cluster component (higher than expected according to its proportion of LULC change). Hence, the transitions showing *ITSC* > 0 can be grouped into the set of transitions with the greatest potential for altering the original structure of the landscape and therefore of most interest for decision-making in landscape management and planning. The higher the ITSC value, the greater the impact on landscape change.

3. Results.

3.1. Land Use/Land Cover Changes (LULCC).

The most important transitions in terms of the area of change in the Lingue basin between 1987 and 2009 are the replacement of native vegetation (SR-NF and Og-NF) and grasslands (Gland) by exotic forest plantations (EFP). This is followed by the replacement of old-growth native forest (Og-NF) and grassland (Gland) by secondary native forest (SR-NF), and the replacement of secondary forest (SR-NF) by grassland (Gland) (Table 1).

Table 1 shows the systematic transitions identified in the Lingue basin between 1987-2009. The table divides these transitions into either productive or natural transitions, of which there are ten each. The higher values resulting from the expression Real-Ref/Ref indicate a stronger effect. For example, the replacement of Secondary Native Forest by Exotic Forest Plantation (SR-NF to EFP) is 3 times higher than would have been expected according to its proportion of LULC change. Major systematic transitions include LULC changes affecting a high percentage of the total basin area (Table 1), e.g., loss of native vegetation to forest plantation (SR-NF to EFP, Og-NF to EFP). However, some LULC transitions that affect a relatively small percentage of the total basin area were also identified as systematic transitions. For instance, shrubland to forest plantations (Sland to EFP), young forest plantations to forest plantations (YH-EFP to EFP) and exotic forest plantations to young forest plantations (EFP to YH-EFP).

[insert table 1]

3.2. Selection of moving window size.

Figure 3 shows the results of our attempts to find the optimal window size for calculating the spatial metrics for the Lingue LULC data. The analysis indicates that the change to mesoscale takes place when window size changes from 900 to 1200 metres, and the *pi* value becomes negative, which means that higher window size will not produce any further changes in the spatial pattern. Thus, any window size of 1200 metres or more would be suitable for calculating the metrics in this domain of scale. In order to maintain a suitable window size for obtaining metrics while keeping the calculation time within reasonable limits, we selected a window size of 1500 metres.

[insert figure3]

3.3. *Maps showing the results of moving window metrics, and maps of significant landscape structure changes.*

Figures 4A to 4D show the percentage of change in SHDI, Naturality, ECON_MN, and IJI from 1987-2009 for the study area as a whole. The images highlight greater alterations in the landscape structure in the north-eastern part of the basin, with substantial losses in diversity and naturality. The central area shows a loss of naturality, although this is combined with increases in diversity and contrast. IJI follows the same pattern as SHDI, although it shows a scattered pattern of smaller, well-defined regions of increase and decrease distributed around the basin. In addition, Figures 4E to 4H show the results of the LISA test for defining spatial clusters of highly autocorrelated values. These represent hotspots of landscape structure change, where losses and gains can be easily identified for each spatial metric between 1987-2009.

[insert figure4]

3.4. *LULCC transitions vs landscape structure changes. ITSC index.*

The relationship between systematic transitions and the spatial cluster of landscape change is represented through the ITSC index. Table 2 shows the calculation of ITSC values for diversity (SHDI) change as an example of one of the four landscape change dimensions. The values in bold type show transitions with a greater impact on landscape structure change than expected according to their proportion of total LULCC in the study area. The results indicate that systematic transitions involving changes to exotic forest plantation (SR-NF to EFP, Og-NF to EFP, Sland to EFP, Gland to EFP) produce a high impact on diversity loss. In 2009, exotic forest plantation became one of the main landscape matrices, producing in some areas a clear homogenization of the landscape. By contrast, the transitions to young exotic forest plantation (EFP to YH-EFP, SR-NF to YH-EFP and to Shrubland (SR-NF to Sland, Og-NF to Sland) increase the value of SHDI, as in some areas they involve the substitution of the natural native forest landscape matrix by new land uses such as forest plantations or shrublands. Another interesting case is the Og-NF to EFP transition, which seems to act in two opposing directions in that it has a high impact on diversity decrease (0.99) and increase (0.48). This effect is due to the partial substitution of natural native forest matrix in some areas which causes an increase in SHDI (new land uses appear in the area), and the removal of remnant patches of natural forest in other areas, which results in the complete removal of the Og-NF, so reducing the SHDI.

[insert table 2]

Table 3 sets out the aggregated results, including ITSC values for all the systematic transitions and landscape dimensions. The values in bold type represent the transitions with a greater impact on landscape structure than expected, while the shaded rows show the transitions that contribute most to landscape structure change (bold values in more than one of the landscape dimensions).

[insert table 3].

4. Discussion.

4.1. LULC changes with the greatest impact on landscape structure change.

The methodology proposed in this study allowed us to identify the contribution made by the different LULC transitions to change in the landscape structure in the Lingue basin between 1987 and 2009. The method delimits spatial clusters of change by applying a LISA test (Anselin et al., 2021) to an image representing the variations in values of spatial landscape metrics. We then developed the ITSC index, assessing significant changes in LULCC using a similar approach to that proposed by Pontius (2004). This new index is useful for determining whether the contribution made by each systematic transition to each spatial cluster of landscape change was higher than expected according to its proportion of total LULCC in the study area.

The results enabled us to identify a specific set of LULC transitions which had the greatest capacity to change the landscape structure in the Lingue basin. For example, the transition from exotic forest plantation (EFP) to young exotic forest plantation (YH-EFP) showed values of 2.47 and 1.52 for ITSC on ECON_MN and IJI gain. This means that this transition has a strong impact on increasing the contrast between the land patches across the landscape, as it involves the replacement of exotic forest plantation (EFP) (a secondary matrix across the landscape) by young/harvested exotic forest plantation (YH-EFP), with almost no tree covering. An important impact can also be seen in the transition from secondary native forest (SR-NF) to young exotic forest plantation (YH-EFP) increasing the contrast of the landscape and the diversity of patches (ITSC ECON_MN gain =1.42 and ITSC SHDI gain=1.89).

Similarly, the transition from Old-growth native forest (Og-NF) to shrubland (Sland) showed high levels of ITSC on SHDI gain (6.46) and ECON_MN loss (2.74). This means that the contribution to the gain in SHDI made by the degradation of old-growth native forest into shrubland was six times higher than expected according to its proportion of total LULCC in the study area, and the contribution to the loss in edge contrast made by the same transition was twice as high. This increase in SHDI is due to the shrinkage of the native forest matrix and the growth in Shrubland patches. Increases in ECON_MN could also be observed in these areas.

Finally, the transition from grassland to wetland (Gland to Wet) showed high levels of ECON gain (ITSC=1.46) and NATUR gain (ITSC=3.36). This is due to the fact that wetlands have high values of naturality and high contrast with other LULC. This transition therefore involves important growth in naturality and contrast when wetlands grow over the surrounding grassland areas.

Therefore, the proposed methodology allowed us to detect both large (high percentage of LULC change) and small transitions (low percentage of LULC) as transitions with a high impact on landscape structure change in terms of diversity, contrast, mixture and naturality. We believe that this is an important finding, as this methodology can provide new tools for studying LULCC. These new tools improve on existing ones, which normally only highlight the transitions with the highest percentages of LULCC within the landscape (Miranda et al., 2017; Zamorano-Elgueta et al., 2015). However, as identified here, transitions with a small percentage of change can have a strong potential impact on landscape structure and produce large transformations in it. These transitions are therefore critical for LULC dynamics analysis in the study area, and must therefore be taken into account in land use planning processes (Duarte et al., 2018).

4.2. Planning implications.

Identifying land use transitions with a high potential for transforming the landscape can provide meaningful insights to help planners identify planning measures that could mitigate landscape structure change. This will be even more relevant in the coming years as Chile is developing planning regulations which give regional governments the competences to create spatial planning policies and plans with mandatory regulations in rural areas (Peña-Cortés et al., 2019). These results could therefore provide a basis for the design of these Plans and for guaranteeing the sustainability of the associated ecosystems (figure 5).

[insert Figure 5].

Some measures may include:

i) Preventing the transformation of extensive areas of native forests (Og-NF) (Figure 5, IA and IB) into Shrublands (Sland), a transition that results in an increase in diversity (SHDI ITSC=6.46) and a decline in edge contrast (ECON ITSC=2.47). The increase in diversity is due to new patches of Sland replacing the natural landscape matrix, while edge contrast loss is due to Sland having less contrast with other LULCs such as Gland or EFP. This also has a high impact in terms of a loss of naturality when Og-NF is replaced by forest plantations of exotic species, (a pattern documented throughout the country, Miranda et al., 2017).

ii) Avoiding massive expansion of young or harvested exotic forest plantations (YH-EFP) (e.g., Figure 5, III), as these transitions involve a strong increase in landscape contrast when substituting EFP (harvest, ITSC = 2.47) or SR-NF (new forest plantations ITSC= 1.42). In addition removing tree and vegetation cover increases erosion and sedimentation (Aburto et al., 2021).

iii) Avoiding transitions from isolated patches of shrubland (Sland) (e.g., Figure 5, IV) to exotic forest plantations (EFP), which reduce diversity (ITSC = 2.82). In areas with high levels of EFP, removing remnant patches of Sland can result in an increase in landscape homogeneity, as EFP becomes the landscape matrix. These patches can also act as habitats for local wildlife, and may evolve into secondary growth native forest (SR-NG) with greater natural value (Echeverria et al., 2006).

iv) Carefully considering the transition from grassland (Gland) (e.g., Figure 5, II) to arable land (Aland) as it involves a high impact in terms of increases in contrasts within the landscape (ITSC=1.61) and IJI (ITSC=2.50), so increasing heterogeneity and mix through new productive patches in natural and seminatural areas. This is because an increase in agriculture based on the extensive use of agrochemicals and monoculture could decrease landscape value (Tudi et al., 2021). However, increasing the mixture of uses with sustainable production of crops and cattle could create multifunctional landscapes, so improving the diversity of wildlife and providing higher quality agricultural products (Rey Benayas et al., 2020).

4.3. Moving window landscape metrics. Advantages and limitations of the proposed methodology.

In this research we have shown how moving window landscape metrics can be used together with LISA analysis to identify the land use transitions with the greatest potential for changing landscape structure within the Lingue basin. Moving windows allowed us to obtain a gradient-based, spatially explicit representation of the metrics, so improving the assessment of landscape structure (Frazier & Kedron, 2017; Lausch et al., 2015). Incorporating a gradient-based representation of landscape metrics can also have beneficial applications in the planning of land use (Lausch et al., 2015), transport (Soria-Lara et al., 2016), and sustainable tourism (Botequilha-Leitão & Diáz-Varela, 2018). In the same way, the pixel-level representation of the values of spatial landscape metrics enables these variables to be integrated into new methods using maps algebra, spatial clusters, and regression models (Rodríguez-Espinosa et al., 2019).

Additionally, identification of the mesoscale through changes in heterogeneity, analyzed by calculating SHDI using moving windows, allowed us to incorporate the scale effect into the analysis (Díaz-Varela et al., 2009). The window size represents the scale at which a given metric is obtained. In this study, the mesoscale threshold of 1200 m was empirically identified, leading us to select 1500 m as the optimum window size for the analysis. In future research, it could be interesting to analyze how sensitive the method proposed here is to different window sizes. Other limitations inherent in using metrics, including those calculated with a moving window, are related to the selection of the metrics used to measure landscape structure (Cushman et al., 2008). There is no consensus as to the most suitable set of metrics, and each study team must choose the ones that best suit their research objectives and their existing knowledge of the landscape.

5. Conclusions.

This study proposes a novel methodological approach for measuring the impact of LULC transitions on structural landscape changes using moving window spatial metrics, LULC systematic transition analysis and spatial clustering. The results for the study area enabled us to conclude that land use changes have a differential impact on landscape structure change and to identify the specific transitions with the greatest impact on landscape structure. Thus, for the same amount of area affected, certain land use changes can result in a greater alteration of the landscape structure, as noted in our study area in southern Chile. The transitions that result in the expansion of Forest Plantations (EFP or YH-FP) have the greatest potential to modify landscape structure (see table 3). Other transitions with a high impact on landscape structure are the substitution of OG-NF for Sland and change from Gland to Aland.

Thus, the proposed methodology shows how moving window spatial metrics, together with an analysis of land use changes, make it possible to identify the systematic processes by which one use is replaced by another, focusing not only on those with the greatest statistical importance (Pontius et al., 2004), but also on those with the greatest potential for altering landscape patterns, so allowing the relevant planning measures to be implemented.

These results can only be obtained using spatially explicit metrics, which express a spatial dimension of the landscape at pixel level, as compared to the studies which use spatial metrics calculated at class or landscape levels (Aguilera et al., 2011). By using the gradient-based model approach (Lausch et al., 2015), we were able to generate maps for the four selected components of landscape structure. These maps were incorporated into the spatial analysis processes using GIS in conjunction with map algebra and spatial cluster analysis. As a result, we obtained measures of the impact of LULC transitions on landscape structure, which form the basis for the development of spatially explicit indicators that enable monitoring over time. This explains why studies that use these spatially explicit tools are becoming increasingly common (Soria-Lara et al., 2016) and need to be developed further.

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REFERENCES.

Aburto, F., Cartes, E., Mardones, O., & Rubilar, R. (2021). Hillslope soil erosion and mobility in pine plantations and native deciduous forest in the coastal range of south-Central Chile. Land Degradation & Development, 32(1), 453-466. https://doi.org/10.1002/ldr.3700

Aguilera, F., Valenzuela, L. M., & Botequilha-Leitão, A. (2011). Landscape metrics in the analysis of urban land use patterns: A case study in a Spanish metropolitan area. Landscape and Urban Planning, 99(3-4), 226-238. https://doi.org/10.1016/j.landurbplan.2010.10.004

Aguilera-Benavente, F., Botequilha-Leitão, A., & Díaz-Varela, E. (2014). Detecting multi-scale urban growth patterns and processes in the Algarve region (Southern Portugal). Applied Geography, 53, 234-245. https://doi.org/10.1016/j.apgeog.2014.06.019

Anselin, L., Li, X., & Koschinsky, J. (2021). GeoDa, From the Desktop to an Ecosystem for Exploring Spatial Data. Geographical Analysis, gean.12311. https://doi.org/10.1111/gean.12311

Arowolo, A. O., & Deng, X. (2018). Land use/land cover change and statistical modelling of cultivated land change drivers in Nigeria. Regional Environmental Change, 18(1), 247-259. https://doi.org/10.1007/s10113-017-1186-5

Bonilla-Bedoya, S., Molina, J. R., Macedo-Pezzopane, J. E., & Herrera-Machuca, M. A. (2014). Fragmentation patterns and systematic transitions of the forested landscape in the upper Amazon region, Ecuador 1990–2008. Journal of Forestry Research, 25(2), 301-309. https://doi.org/10.1007/s11676-013-0419-9

Botequilha Leitão, A., & Ahern, J. (2002). Applying landscape ecological concepts and metrics in sustainable landscape planning. Landscape and Urban Planning, 59(2), 65-93. https://doi.org/10.1016/S0169-2046(02)00005-1

Botequilha-Leitão, A., & Diáz-Varela, E. (2018). An alternative planning paradigm for coastal landscapes and tourism. Spatial metrics as indicators for planning coastal tourism landscapes. Tourism & Management Studies, 14(1), 45-57. https://doi.org/10.18089/tms.2018.14104

Chavez, P. S. (1996). Image-Based Atmospheric Corrections—Revisited and Improved. Photogrammetric Engineering and Remote Sensing, 62, 1025-1035.

Cushman, S. A., & Landguth, E. L. (2010). Scale dependent inference in landscape genetics. Landscape Ecology, 25(6), 967-979. https://doi.org/10.1007/s10980-010-9467-0

Cushman, S. A., McGarigal, K., & Neel, M. C. (2008). Parsimony in landscape metrics: Strength, universality, and consistency. Ecological Indicators, 8(5), 691-703. https://doi.org/10.1016/j.ecolind.2007.12.002

Di Castri, F., & Hajek, E. R. (1976). Bioclimatología de chile (Vol. 128). Vicerrectoría Académica de la Universidad Católica de Chile Santiago.

Díaz-Varela, E., Álvarez-López, C. J., & Marey-Pérez, M. F. (2009). Multiscale delineation of landscape planning units based on spatial variation of land-use patterns in Galicia, NW Spain. Landscape and Ecological Engineering, 5(1), 1-10. https://doi.org/10.1007/s11355-008-0053-4

Diaz-Varela, E., Roces-Díaz, J.V., & Álvarez-Álvarez, P. (2016). Detection of landscape heterogeneity at multiple scales: Use of the Quadratic Entropy Index. Landscape and Urban Planning, 153, 149-159. https://doi.org/10.1016/j.landurbplan.2016.05.004

Duarte, G. T., Santos, P. M., Cornelissen, T. G., Ribeiro, M. C., & Paglia, A. P. (2018). The effects of landscape patterns on ecosystem services: Meta-analyses of landscape services. Landscape Ecology, 33(8), 1247-1257. https://doi.org/10.1007/s10980-018-0673-5

Ducci, L., Agnelli, P., Di Febbraro, M., Frate, L., Russo, D., Loy, A., ... & Roscioni, F. (2015). Different bat guilds perceive their habitat in different ways: a multiscale landscape approach for variable selection in species distribution modelling. Landscape ecology, 30, 2147-2159. https://doi.org/10.1007/s10980-015-0237-x

Echeverria, C., Coomes, D., Salas, J., Rey-Benayas, J. M., Lara, A., & Newton, A. (2006). Rapid deforestation and fragmentation of Chilean Temperate Forests. Biological Conservation, 130(4), 481-494. https://doi.org/10.1016/j.biocon.2006.01.017

Foody, G. M. (2008). Harshness in image classification accuracy assessment. International Journal of Remote Sensing, 29(11), 3137-3158. https://doi.org/10.1080/01431160701442120

Frazier, A. E., & Kedron, P. (2017). Landscape Metrics: Past Progress and Future Directions. Current Landscape Ecology Reports, 2(3), 63-72. https://doi.org/10.1007/s40823-017-0026-0

Galletti, C. S., Turner, B. L., & Myint, S. W. (2016). Land changes and their drivers in the cloud forest and coastal zone of Dhofar, Oman, between 1988 and 2013. Regional Environmental Change, 16(7), 2141-2153. https://doi.org/10.1007/s10113-016-0942-2

García-Llamas, P., Geijzendorffer, I. R., García-Nieto, A. P., Calvo, L., Suárez-Seoane, S., & Cramer, W. (2019). Impact of land cover change on ecosystem service supply in mountain systems: A case study in the Cantabrian Mountains (NW of Spain). Regional Environmental Change, 19(2), 529-542. https://doi.org/10.1007/s10113-018-1419-2

Grimm, N. B., Faeth, S. H., Golubiewski, N. E., Redman, C. L., Wu, J., Bai, X., & Briggs, J. M. (2008). Global Change and the Ecology of Cities. Science, 319(5864), 756-760. https://doi.org/10.1126/science.1150195

Hagen-Zanker, A. (2016). A computational framework for generalized moving windows and its application to landscape pattern analysis. International Journal of Applied Earth Observation and Geoinformation, 44, 205-216. https://doi.org/10.1016/j.jag.2015.09.010

Hermann, A., Schleifer, S., & Wrbka, T. (2011). The Concept of Ecosystem Services Regarding Landscape Research: A Review. Living Reviews in Landscape Research, 5. https://doi.org/10.12942/lrlr-2011-1

Hermosilla-Palma, K., Pliscoff, P., & Folchi, M. (2021). Sixty years of land-use and land-cover change dynamics in a global biodiversity hotspot under threat from global change. Journal of Land Use Science, 16(5-6), 467-478. https://doi.org/10.1080/1747423X.2021.2011970

Lara, A., Little, C., Urrutia, R., McPhee, J., Álvarez-Garretón, C., Oyarzún, C., Soto, D., Donoso, P., Nahuelhual, L., Pino, M., & Arismendi, I. (2009). Assessment of ecosystem services as an opportunity for the conservation and management of native forests in Chile. Forest Ecology and Management, 258(4), 415-424. https://doi.org/10.1016/j.foreco.2009.01.004

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R.-U., Tischendorf, L., & Walz, U. (2015b). Understanding and quantifying landscape structure – A review on relevant process characteristics, data models and landscape metrics. Ecological Modelling, 295, 31-41. https://doi.org/10.1016/j.ecolmodel.2014.08.018

Lebdioui, A. (2019). Chile's Export Diversification since 1960: A Free Market ? Development and Change, 50(6), 1624-1663. https://doi.org/10.1111/dech.12545

Lv, J., Ma, T., Dong, Z., Yao, Y., & Yuan, Z. (2018). Temporal and spatial analyses of the landscape pattern of Wuhan city based on remote sensing images. ISPRS International Journal of Geo-Information, 7(9), 340. https://doi.org/10.3390/ijgi7090340

Miranda, A., Altamirano, A., Cayuela, L., Lara, A., & González, M. (2017). Native forest loss in the Chilean biodiversity hotspot: Revealing the evidence. Regional Environmental Change, 17(1), 285-297. https://doi.org/10.1007/s10113-016-1010-7

Peña-Cortés, F., Escalona, M., Soria-Lara, J. A., Pincheira-Ulbrich, J., Salinas-Silva, C., & Alarcón, F. (2020). Translating sociocultural transformations into historical maps on land use changes: The case of Lafkenmapu (Araucanía, Chile). Journal of Maps, 16(1), 163-171. https://doi.org/10.1080/17445647.2020.1793817

Peña-Cortés, F., Rebolledo, G., Hermosilla, K., Hauenstein, E., Bertrán, C., Schlatter, R., & Tapia, J. (2006). Dinámica del paisaje para el período 1980-2004 en la cuenca costera del Lago Budi, Chile. Consideraciones para la conservación de sus humedales. Ecología Austral, 14.

Peña-Cortés, F., Vergara-Fernández, C., Pincheira-Ulbrich, J., Aguilera-Benavente, F., & Gallardo-Alvarez, N. (2021). Location factors and dynamics of tree plantation expansion in two coastal river basins in south-central Chile: Basis for land use planning. Journal of Land Use Science, 16(2), 159-173. https://doi.org/10.1080/1747423X.2021.1882597

Pontius, R. G., Shusas, E., & McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems & Environment, 101(2-3), 251-268. https://doi.org/10.1016/j.agee.2003.09.008

Rey Benayas, J. M., Altamirano, A., Miranda, A., Catalán, G., Prado, M., Lisón, F., & Bullock, J. M. (2020). Landscape restoration in a mixed agricultural-forest catchment: Planning a buffer strip and hedgerow network in a Chilean biodiversity hotspot. Ambio, 49(1), 310-323. https://doi.org/10.1007/s13280-019-01149-2

Rodríguez-Espinosa, V. M., Aguilera-Benavente, F., & Gómez-Delgado, M. (2019). Green infrastructure design using GIS and spatial analysis: A proposal for the Henares Corridor (Madrid-Guadalajara, Spain). Landscape Research, 45(1), 26-43. https://doi.org/10.1080/01426397.2019.1569221

Song, X.-P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. Nature, 560(7720), 639-643. https://doi.org/10.1038/s41586-018-0411-9

Soria-Lara, J. A., Aguilera-Benavente, F., & Arranz-López, A. (2016). Integrating land use and transport practice through spatial metrics. Transportation Research Part A: Policy and Practice, 91, 330-345. https://doi.org/10.1016/j.tra.2016.06.023

Tudi, M., Daniel Ruan, H., Wang, L., Lyu, J., Sadler, R., Connell, D., Chu, C., & Phung, D. T. (2021). Agriculture Development, Pesticide Application and Its Impact on the Environment. International Journal of Environmental Research and Public Health, 18(3), 1112. https://doi.org/10.3390/ijerph18031112

Wu, J., Jenerette, G. D., Buyantuyev, A., & Redman, C. L. (2011). Quantifying spatiotemporal patterns of urbanization: The case of the two fastest growing metropolitan regions in the United States. Ecological Complexity, 8(1), 1-8. https://doi.org/10.1016/j.ecocom.2010.03.002

Wang, R., Feng, Y., Tong, X., Zhao, J., & Zhai, S. (2021). Impacts of spatial scale on the delineation of spatiotemporal urban expansion. Ecological Indicators, 129, 107896. https://doi.org/10.1016/j.ecolind.2021.107896

Zamorano-Elgueta, C., Rey Benayas, J. M., Cayuela, L., Hantson, S., & Armenteras, D. (2015). Native forest replacement by exotic plantations in southern Chile (1985–2011) and partial compensation by natural regeneration. Forest Ecology and Management, 345, 10-20. https://doi.org/10.1016/j.foreco.2015.02.025