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Evidence for deviations from uniform changes along river basin, estuarine, and adjacent coastal areas in a Portuguese watershed illustrated by CORINE maps: an Intensity Analysis approach

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Abstract

We apply a method to evaluate the strength of the evidence for deviations from uniform land change in a coastal area, in the context of Intensity Analysis. The errors in the CORINE maps at 1990 and 2006 can influence the apparent change, but the errors are unknown because error assessment of the 1990 map has never been released, while the error of the 2006 map has been checked for only some countries. The 1990 and the 2006 maps of a coastal watershed in Portugal served as the data to compute the intensities of changes among eight categories. We evaluate the sizes and types of errors that could explain deviations from uniform intensities. Errors in 2.0% of the 2006 map can explain all apparent deviations from uniform gains. Errors in 1.5% of the 1990 map can explain all apparent deviations from uniform losses. Errors in less than 0.7% of the 1990 map can explain all apparent deviations from uniform transitions to each gaining category. We analyse the strength of the evidence for deviations from uniform intensities in light of historical processes of change. Historical processes can explain some transitions that the data show, while the hypothesized errors in the data are the explanation for other transitions that are not consistent with known processes. Inconsistent transitions are an indication of the misclassification errors that could propagate to other land cover change applications, as in the assessment of hydrological processes.

Keywords: Accuracy, land cover, transitions, indicator, watershed, coastal system, hydrologic processes

1. Introduction

The increasing demand for land and water resources in coastal areas (Freire et al., 2009) has triggered land cover changes imposing pressures on coastal systems (Palmer et al., 2011). The impacts of land change include changes in water supply from alterations in the processes of runoff, infiltration and groundwater recharge (Ampe et al., 2012; Sajikumar and Remya, 2015; Yang et al., 2015); changes in water demands from changes in land use practices (Priess et al., 2011); and changes in water quality from urban growth, industrial development and agricultural runoff (León-Muñoz et al., 2013; Mouri et al., 2011; Seeboonruang, 2012).

The assessment of impacts in the water balance and quality may have consequences in coastal management and thus requires accurate interpretation of land cover changes (LCC), for which the accuracies of land cover maps at two time points and the map of change are key elements (Loosvelt et al., 2014). However, accuracy assessment has not always been considered in the interpretation of LCC (Kuemmerle et al., 2009). The error pattern observed in a LCC map reflects the errors at the first time point as well as their interactions with the errors at the second time point. The error of the map of change is expected to be greater than the error of either of the two maps from which it derives (Burnicki, 2011). The change-detection error matrix is the most reported error assessment tool (Foody, 2010), but important advances are still under development (Aldwaik and Pontius, 2013; Burnicki, 2011; Liu and Zhou, 2004; Zhang and Tang, 2012).

The CORINE Land Cover (CLC) products are a series of land cover maps developed and released by the European Environment Agency since the 1990s. Three maps are currently available (CLC1990, CLC2000 and CLC2006), and one more is under development (CLC2012) (EEA, 2012). CLC maps have been used widely for land cover change assessment, not only at the European level (Feranec et al., 2010), but also at the level of regions (Hewitt and Escobar, 2011), river basin catchments (Teixeira et al., 2014), coastal zones (Freire et al., 2009) and bio-geographic areas (Kozak et al., 2007). The accuracy assessment of CLC maps has been standardized and reported, but only after the CLC1990 map. There is no available information regarding the accuracy of the CLC1990 map and the accuracy assessment of the CLC2006 has been checked for only some countries (Büttner et al., 2012; Caetano et al., 2009). Feranec et al. (2010) assessed land cover change in Europe using CORINE Land Cover at 1990 and 2000, then interpreted the results in light of the accuracies of the individual land categories in the single 2000 map. The possible error at 1990 was ignored by Feranec et al. (2010) though no explanation was provided.

Higher single map accuracies are expected to create higher accuracy in the map of change (Feranec et al., 2010), but if accuracy information is unavailable or imprecise, then how can we evaluate the influence of classification errors on land change assessments? The answer depends on the method of assessment. Aldwaik and Pontius (2012) proposed a method for land change assessment, called Intensity Analysis, which computes deviations between observed changes and uniform changes. Aldwaik and Pontius (2013) give a method to compute the minimum hypothetical error that could account for those deviations between observed changes and uniform changes. In this article, we compute the size of the hypothetical errors that could account for the deviations between the observed intensities and the corresponding uniform intensity. If the hypothetical errors are small, then the evidence for deviations from uniform intensities is weak. Our work is based on the hypothesis that if no known historical processes of change can explain the deviations from uniform intensities, then the apparent changes are misclassification errors that could propagate to other land cover map applications, as in the assessment of processes affecting water supply, demand and quality (Loosvelt et al., 2014). Our main objectives are thus to quantify hypothetical errors and to describe a framework to explain counter-intuitive deviations that could hinder our perception of the hydrologic problems affecting river basins and consequently influence the development of plans for the management of water quantity and quality.

We use the CLC1990 and CLC2006 maps of eight land categories to examine change in the Mondego river basin, which is a coastal watershed in Portugal. In a previous study of the same Basin, Teixeira et al. (2014) applied a methodology proposed by Pontius et al. (2004), but changes at the category level were not evaluated, accuracies of the CLC maps were ignored and the disagreement between maps of different time points was the only statistic reported. This previous study was important for the management of land-water interaction, therefore we use the same data to demonstrate the ability of Intensity Analysis and its associated error measures to interpret land change patterns. The results from Teixeira et al. (2014) indicated lack of uniformity for the transition intensities across losing categories, given a particular category's gain, and across gaining categories, given a particular category's loss. Our present manuscript refrains from analysing transition intensities given a category's loss, thus refrains from using the word "systematic", based on the advice of Pontius et al. (2013) and Enaruvbe and Pontius (2015).

1.1. CORINE Land Cover

The CLC1990_PT (for Portugal), hereafter just CLC1990, was produced based on satellite images from the years 1985/86/87. It was initially a pilot project and experienced several modifications since it was first released. The accuracy of the CLC1990 map was assessed, but the assessment report is not available. Büttner et al.

(2012) state that a thematic accuracy of at least 85% was probably not achieved. Between 2002 and 2005, geometric and thematic corrections were implemented and a revised product was generated (Caetano et al., 2005). Though the CLC1990 base data corresponds to three different time points, we assumed that the changes that might have occurred during the three consecutive years are negligible. Land persistence tends to dominate landscapes (Pontius et al., 2004) and the Mondego river basin is an example of this phenomenon (Teixeira et al., 2014).

The CLC2006_PT, hereafter just CLC2006, was produced following a first approach to change mapping (Caetano et al., 2009). According to this approach, the revision and correction of the CLC2000 map was performed simultaneously with the visual interpretation of images at both 2000 and 2006. Afterwards, the CLC2006 map was derived based on the intersection of the revised CLC2000 and the change map (CLC-Changes$_{2000\text{-}2006}$) (Büttner et al., 2004; Caetano et al., 2009). Delineation of changes was based on the polygons of the CLC2000 map to avoid the creation of sliver polygons when performing intersection (Caetano et al., 2009). The Portuguese CLC2006 map has an estimated overall accuracy percentage of 90.2±1.3 at the 95% confidence level (Caetano et al. 2009). Overall accuracy is the proportion of the spatial extent that has agreement between the map and the ground, combined over all categories; whereas both user's and producer's accuracies refer to individual categories. User's accuracy of a category is the area of agreement for the category divided by the area of the category on the map. Producer's accuracy of a category is the area of agreement for the category divided by the area of the category on the ground. Regarding user's accuracies, only five categories (231, 132, 222, 313 and 332) out of the forty-four level 3 categories have 95% confidence intervals that lie completely below the minimum goal of 85 percent. Regarding producer's accuracies, only two categories (231 and 423) have 95%

confidence intervals entirely below 85 percent (Caetano et al., 2009). One of the key issues affecting land cover configuration and composition is the minimum mapping unit (MMU). The MMU of CLC maps is set to 25 ha, which is attained through generalisation procedures (Caetano et al., 2009; EEA, 2007). The minimum distance between lines is set to 100 m. Spatial generalisation reduces the complexity of the data structure, influencing both location and attribute accuracy as a result of reclassification, aggregation, amalgamation (technical-unreal change), boundary smoothing and simplification (Congalton, 1997).

The raster format of the CLC maps was used in this study. Though the conversion from vector to the raster might be another source of error, the positional errors near boundaries (Foody, 2002) introduced by the raster model used to generate the CLC raster files are not substantial, because the pixel size of 1 ha is much smaller than the MMU of 25 ha (EEA, 2007).

1.2. Intensity Analysis

Intensity Analysis compares observed intensities of changes to a uniform intensity (Aldwaik & Pontius 2012, 2013; Pontius et al. 2013). Intensity Analysis has three levels of detail: interval, category and transition. The interval level examines overall change during each time interval for cases with more than two time points. The category level examines each category’s gross gain and gross loss. The transition level examines intensities of transitions from losing categories to any particular gaining category. Each level has its own uniform hypothesis that the change intensity is uniform across intervals, categories and transitions.

Intensity Analysis quantifies the deviation between an observed intensity and the uniform intensity. Map error might account for the calculated difference between an observed intensity and the uniform intensity. If the observed intensity is greater than the uniform intensity, then the data show more change than the uniform hypothesis implies and thus a hypothetical commission error is calculated. Commission error intensity is the complement of User's accuracy. In contrast, if the observed intensity is smaller than the uniform intensity, then the data show less change than the uniform hypothesis implies and thus a hypothetical omission error is calculated. Omission error intensity is the complement of Producer's accuracy. Larger hypothetical errors give weaker evidence that true change is uniform.

1.3. Mondego river basin case study

The Mondego river basin is located in the central region of Portugal, Europe (Fig. 1). The studied river basin has an area of 6658 square kilometres and a NE–SW orientation. It encompasses 36 municipalities with an estimated population of 165 inhabitants per square kilometre (INE 2014). The river basin is occupied mainly by agricultural and forest areas that are distributed throughout the basin, whereas urban and industrial areas are located mainly on the coastal strip (Teixeira et al., 2014). Coimbra and Figueira da Foz are two of the most populated municipalities, and they play an important role within the Mondego river dynamics because they have grown along the river margins.

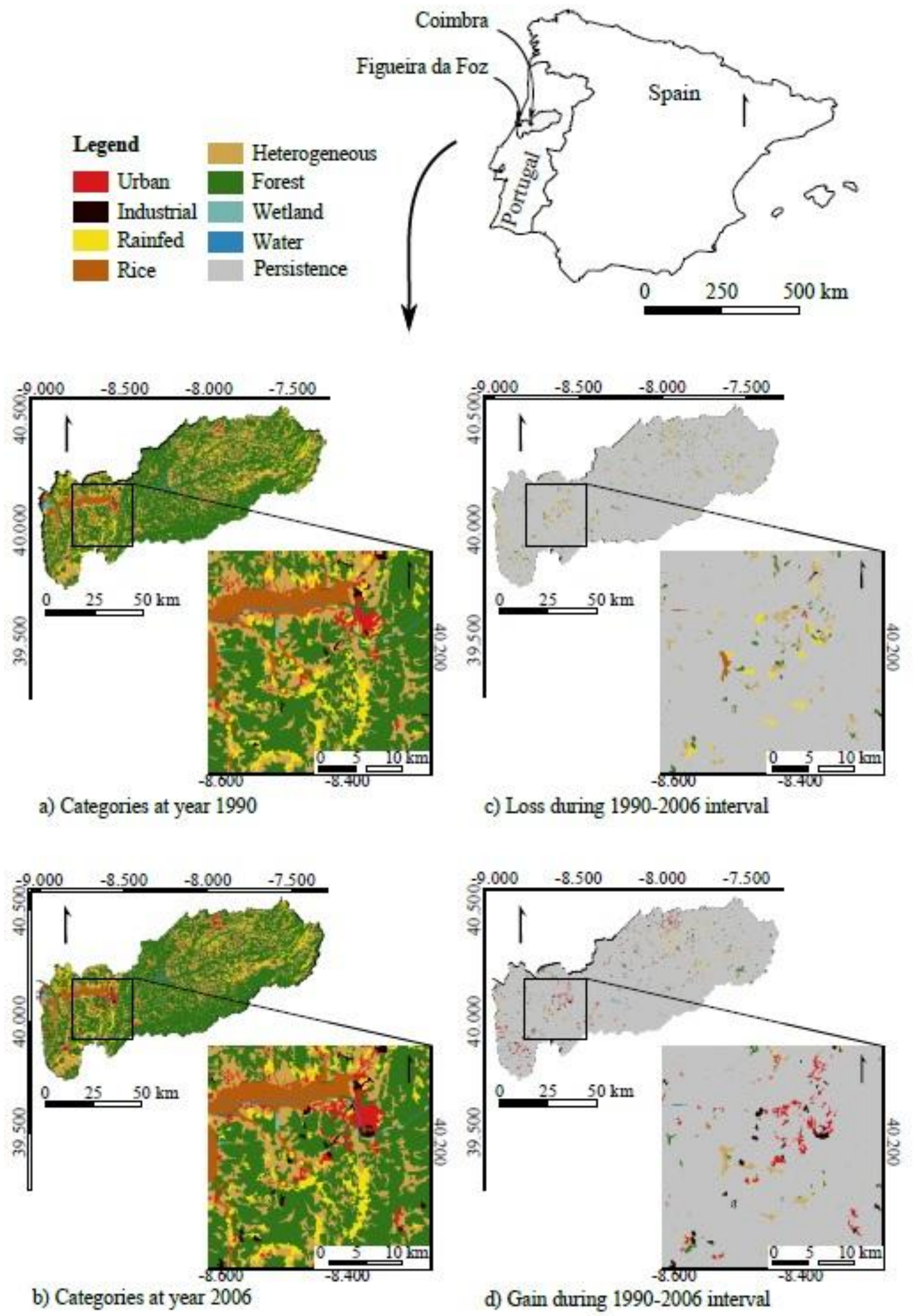

Figure 1. Map in the upper right shows the location of the study site in the centre of Portugal. The study site is the Mondego river basin. The four lower maps on the left show land-cover categories at 1990 and 2006 in the entire river basin and in a small portion of the study site. Maps on the right show changes during 1990-2006 in the entire river basin and in a small portion of the study site. Tonalities other than grey in figure 1.c identify category losses during the time interval. Tonalities other than grey in figure 1.d identify category gains during the time interval.

2. Methodology

2.1. Land cover dataset

The analysis was performed using CORINE Land Cover raster data, resolution 100×100 m, for the 1990 and 2006 inventories (EEA, 2012). The same eight categories analysed by Teixeira et al.(2014) are evaluated in the present manuscript: urban (Urban - U), industrial (Industrial - I), rainfed and permanent crops (Rainfed - R), permanently irrigated and rice fields (Rice - P), heterogeneous agriculture (Heterogeneous - H), forest (F), wetland (W) and water bodies (Water - B). Teixeira et al. (2014) describe how the 44 CORINE categories were reclassified to these eight categories.

2.2. Intensity Analysis and hypothetical error

A transition matrix was produced for the time interval 1990-2006. Table 1 gives the Mathematical notation. Equation 1 gives overall change during the time interval.

Table 1. Mathematical notation for Intensity Analysis

Symbol	Meaning
J	number of categories
i	index for a category at the interval's initial time point
j	index for a category at the interval's final time point
n	index for the gaining category for the selected transition
Cij	number of pixels that transition from category *i* to category *j*
S	overall change as percent of the spatial extent, which equals the uniform intensity for the category level
Gj	intensity of gain of category *j* relative to size of category *j* at final time
Li	intensity of loss of category *i* relative to size of category *i* at initial time
Rin	intensity of transition from category *i* to category *n*, relative to size of category *i* at initial time where *i*≠*n*
Wn	uniform intensity of transition from all non-*n* categories to category *n*, relative to size of all non-*n* categories at the initial time

$$S = \frac{\sum_{j=1}^{J}\left\{\left(\sum_{i=1}^{J} C_{ij}\right) - C_{jj}\right\} 100\%}{\sum_{j=1}^{J}\sum_{i=1}^{J} C_{ij}} \qquad (1)$$

2.2.2. Category level

Equation 2 gives gross gain intensities and Equation 3 gives gross loss intensities. These are compared to the uniform intensity of change from Equation 1. If all land categories were to gain and to lose with the same intensity given the size of overall change, then category gain intensities (*Gj*) and loss intensities (*Li*) would equal the overall intensity *S*. If *Gj* > *S*, then category *j* is an active gainer; and if *Li* > *S*, then category *i* is an active loser. If *Gj* < *S*, then category *j* is a dormant gainer; and if *Li* < *S*, then category *i* is a dormant loser.

$$G_j = \frac{\{\text{area of gain of } j\}100\%}{\text{area of } j \text{ at } t{+}1} = \frac{\left\{\left(\sum_{i=1}^{J} C_{ij}\right) - C_{jj}\right\}100\%}{\sum_{i=1}^{J} C_{ij}} \quad (2)$$

$$L_i = \frac{\{\text{area loss of } i\}100\%}{\text{area } i \text{ at } t} = \frac{\left\{\left(\sum_{j=1}^{J} C_{ij}\right) - C_{ii}\right\}100\%}{\sum_{j=1}^{J} C_{ij}} \quad (3)$$

If *Gj* > *S*, then equation 4 gives the hypothesised commission error intensity of category *j* at the final time. If *Gj* < *S*, then equation 5 gives the hypothesised omission error intensity of category *j* at the final time.

$$\text{Commission of } j \text{ intensity at final time} = \frac{\left(\sum_{i=1}^{J} C_{ij}\right)(G_j - S)/100\% - S}{\left(\sum_{i=1}^{J} C_{ij}\right) - C_{jj}} 100\% \quad (4)$$

$$\text{Omission of } j \text{ intensity at final time} = \frac{\left(\sum_{i=1}^{J} C_{ij}\right)(S - G_j)/100\% - S}{\left\{\left(\sum_{i=1}^{J} C_{ij}\right) - C_{jj}\right\} + \left\{\left(\sum_{i=1}^{J} C_{ij}\right)(S - G_j)/100\% - S\right\}} 100\% \quad (5)$$

If *Li* > *S*, then equation 6 gives the hypothesised commission error intensity of category *i* at the initial time. If *Li* < *S*, then equation 7 gives the hypothesised omission error intensity of category *i* at the initial time.

$$\text{Commission of } i \text{ intensity at initial time} = \frac{\left(\sum_{j=1}^{J} C_{ij}\right)(L_i - S)/100\% - S}{\left(\sum_{j=1}^{J} C_{ij}\right) - C_{ii}} \quad (6)$$

$$\textbf{Omission of } i \textbf{ intensity at initial time} = \frac{\left(\sum_{j=1}^{J} C_{ij}\right)(S-L_i)/100\% - S}{\left\{\left(\sum_{j=1}^{J} C_{ij}\right) - C_{ii}\right\} + \left\{\left(\sum_{j=1}^{J} C_{ij}\right)(S-L_i)/100\% - S\right\}} \quad (7)$$

2.2.3. Transition level

We consider the transition from an arbitrary category *i* to a particular gaining category *n*. Equation 8 gives the observed intensity of transition from *i* to *n* relative to the size of *i* at the initial time. Equation 9 gives the hypothesised uniform intensity for the gain of category *n*. If *n* were to gain with the same intensity from all non-*n* categories, then the uniform intensity *Wn* would equal *Rin* for all *i*. If *Rin* > *Wn*, then the gain of *n* targets *i*. If *Rin* < *Wn*, then the gain of *n* avoids *i*.

$$R_{in} = \frac{\{\text{area of transition from } i \text{ to } n\}100\%}{\text{area of } i \text{ at } t} = \frac{\{C_{in}\}100\%}{\sum_{j=1}^{J} C_{ij}} \quad (8)$$

$$W_n = \frac{\{\text{area of gain of } n\}100\%}{\text{area of } j \text{ at } t+1} = \frac{\left\{\left(\sum_{i=1}^{J} C_{in}\right) - C_{nn}\right\}100\%}{\sum_{j=1}^{J}\left\{\left(\sum_{i=1}^{J} C_{ij}\right) - C_{nj}\right\}} \quad (9)$$

If *Rin* > *Wn*, then equation 10 gives the hypothesised commission error intensity of category *i* at the initial time that could account for the deviation from uniform. If *Rin* < *Wn*, then equation 11 gives the hypothesised omission error intensity of category *i* at the initial time that could account for the deviation from uniform.

$$\textbf{Commission of } i \textbf{ intensity at initial time} = \frac{\left(\sum_{j=1}^{J} C_{ij}\right)(R_{in}-W_n)/100\% - W_n}{C_{in}} 100\% \quad (10)$$

$$\textbf{Omission of } i \textbf{ intensity at initial time} = \frac{\left(\sum_{j=1}^{J} C_{ij}\right)(W_n-R_{in})/100\% - W_n}{\left\{\left(\sum_{j=1}^{J} C_{ij}\right)(W_n-R_{in})/100\% - W_n\right\} + (C_{in})} 100\% \quad (11)$$

3. Results

3.1. Category level

Figure 2.a shows the gain intensity of each category. Five categories are active gainers: urban, industrial, rainfed, wetland and water. The remaining categories are dormant gainers: rice, heterogeneous and forest. Figure 2.b shows a segmented bar for the gain of each category. If the category is active, then the size of the gain is the sum of its two segments, which are its black segment and a commission segment. If the category is dormant, then the size of the gain is the black segment, which is accompanied by an omission segment. For example, if change were uniform, then urban would have gained 301 pixels, but the observed urban gain was 7986 pixels. The difference could be explained by commission of urban error for 7685 pixels at 2006. If change were uniform, then forest would have gained 16873 pixels, but forest actually gained 5176 pixels. The difference could be explained by omission of forest error for 11697 pixels at 2006. We assume each pixel of error is commission of an active category and omission of a dormant category, thus the size of all the commission errors equals the size of all the omission errors in figure 2.b. Errors on 2.0% of the 2006 map could account for all deviations from uniform gains.

Figure 2.c shows the loss intensity of each category. Three categories are active losers: industrial, rainfed, heterogeneous. The remaining categories are dormant losers. Figure 2.d shows a segmented bar for the loss of each category. If the category is active, then the size of the loss is the sum of its two segments, which are its black segment and a commission segment. If the category is dormant, then the size of the gain is the black segment, which is accompanied by an omission segment. For example, if change were uniform, then forest would have lost 16873 pixels, but forest actually lost 7396 pixels.

Omission of forest error on 9477 pixels at 1990 could account for the difference. Errors on 1.5% of the 1990 map could account for all deviations from uniform losses.

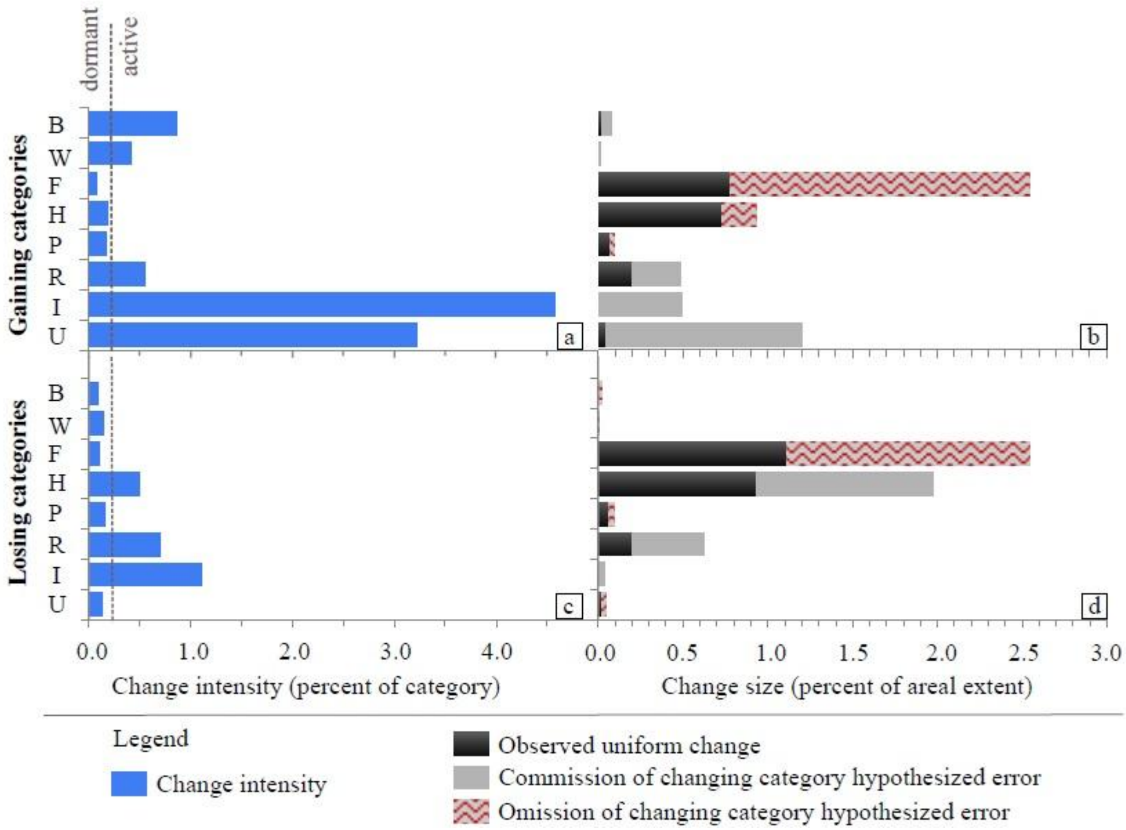

Figure 2. Intensity of a) gains and c) losses by category. Gain intensity is a percentage of the category at 2006, while loss intensity is a percentage of the category at 1990. The dashed line is the uniform change intensity. Sizes of the gains and losses along with hypothetical errors that could account for deviations from uniform category level b) gains and d) losses. U-urban, I-industrial, R-rainfed and permanent crops, P-Permanently irrigated and rice fields, H-heterogeneous agriculture, F-forest, W-wetland, B-water bodies.

3.2. Transition level

Figure 3 shows the results of the transition level analysis for each gaining category. Each gaining category has a pair of graphs. Figures 3.a-b show graphs for urban gain, figures 3.c-d show graphs for industrial gain, etc. The first graph in each pair shows the transition intensity, while the second graph in each pair shows the transition size. If the transition intensity from a particular losing category is greater than the uniform intensity, then we say the gaining category targets that particular losing category. If the transition intensity from a particular losing category is less than the uniform intensity, then we say the gaining category avoids that particular losing category. For example, figure 3.a shows that the gain of urban targets industrial, rainfed and heterogeneous, while avoids the remaining categories.

The graphs concerning transition size indicate the hypothetical errors in the 1990 map that could account for deviations between uniform and observed transition intensities. Figure 3.b shows that hypothetical error on 0.7% of the areal extent could account for deviations from uniform transitions to urban, where the errors are simultaneously commission of industrial, rainfed and heterogeneous and omission of rice, forest, wetland and water. For each other gaining category, errors on less than 0.7% of the areal extent could account for all other deviations from uniform transitions.

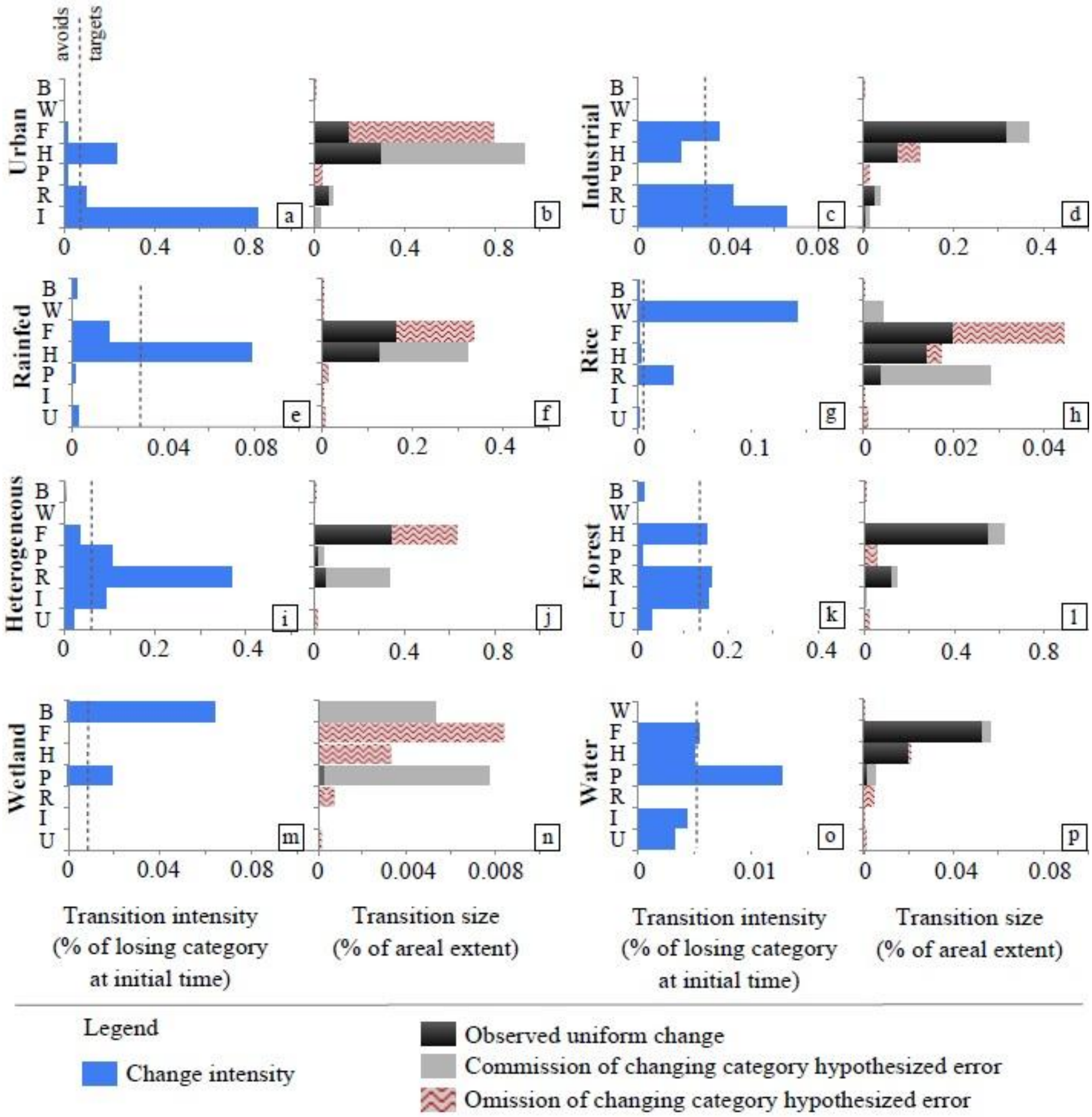

Figure 3. Transition intensity for the gain of: a) urban, c) industrial, e) rice, g) rainfed, i) heterogeneous, k) forest, m) wetland, o) water. The dashed vertical line indicates the uniform transition intensity, given the category's gain. Sizes of the transitions along with hypothetical errors at 1990 that could account for deviations from uniform intensities for the gain of: b) urban, d) industrial, f) rice, h) rainfed, j) heterogeneous, l) forest, n) wetland, p) water. U-urban, I-industrial, R-rainfed and permanent crops, P-Permanently irrigated and rice fields, H-heterogeneous agriculture, F-forest, W-wetland, B-water bodies.

4. Discussion

4.1. Counter-intuitive results

Results indicate that the urban category is active in terms of gains. Data from the National Statistical Institute indicate that house holding increased in Portugal, at least since 2001 (INE 2014), which is expected in a context of rapid economic growth, such as the one occurred in Portugal between 1990 and 2006 (Amaral, 2011). Given what we know about urban development and its most probable trends, we consider it plausible that urban is truly active in gains, regardless of possible map error. However, counter-intuitively, the transition level intensities show that the gain of urban seems to target industrial more intensively than heterogeneous or rainfed. We expect urban areas to grow more from heterogeneous because developers tend to overtake farming or rural open space around major growth centres (Delbecq and Florax, 2010; Ives and Kendal, 2013). In fact, the hypothesised commission error at 1990 of heterogeneous is larger than the hypothesized commission error of rainfed and industrial at 1990, which reflects the fact that the area of the transition from heterogeneous to urban is larger than the area of the transition from industrial to urban (Fig. 3.b). Also, due to spectral similarity, urban and industrial are categories that could be easily confused during the mapping process (Su and Du, 2011). It is plausible that the river basin has substantial error of simultaneous omission of urban and commission of industrial in the 1990 map. In such situation, the commission of industrial at 1990 on 0.002% of the areal extent could account for urban appearing to target industrial. This 0.002% hypothetical error would account for 92.2% of the apparent transition from industrial to urban.

Results also indicate that industrial is active in terms of gains. Though this could be consistent with a period of economic prosperity (Duarte et al., 2013), the evolution of the economic sectors' structure in Portugal indicates that this is not plausible. Between

1986 and 2008, the gross domestic product (GDP) increased approximately 4% per year in Portugal (INE, 2014), but during the same period the gross value added (GVA) related to the primary sector decreased from 10% to 2%, the GVA related to the industrial sector decreased from 29% to 17% and the GVA related to the services' economic sector increased from 55% to 73% (Mateus, 2013). This reflects a process of deindustrialization, i.e. loss of the relative importance of industry, associated with a shift from the primary and secondary sectors to the services' sector of the economy. In this case, the hypothetical commission error of industrial at 2006 on 0.487% of the areal extent could account for industrial's gain appearing active. This hypothetical error would account for 98.5% of industrial's apparent gain.

Results also indicate that industrial gain targets urban with more intensity than rainfed or forest. Information is scarce regarding the location and year of construction of industrial parks and large industrial units in our study area, thus we were not able to identify whether this transition intensity is plausible and we consider it would need further analysis. We know that several industrial parks and large industrial units that have been built in recent years, are located outside of the urban areas' centre. Nevertheless, it is unknown whether these industrial areas have been built more over degraded and discontinuous urban areas, over agricultural areas or over legally unconstrained forest areas. However, it would again be plausible to assume that due to spectral similarity, urban and industrial might have been confused during the mapping process (Su and Du, 2011), causing substantial error of omission of urban and commission of industrial in the 1990 map. In this situation, the commission of urban at 1990 on 0.006% of the areal extent could account for industrial appearing to target urban. This 0.006% hypothetical error would account for 53.3% of the apparent transition from industrial to urban.

The gain of water targeting forest is another counter-intuitive result considering the temporal changes in the Mondego river basin. The transition from forest to water would be expected with the construction of dams. In fact, the set of interventions under the Hydraulic Harnessing plan for the Mondego basin included the construction of upstream dams for flood control and power generation, namely the Aguieira-Raiva dam and the Fronhas dam, which began to operate before 1986 (LNEC, 2012)(LNEC-Laboratório Nacional de Engenharia Civil. Departamento de Hidráulica e Ambiente, 2012). Thus, it would be expected that these dams would already be identified in the 1990 map. However, the Fronhas dam, currently with 535 ha and operating since 1985, is not identified. We hypothesise that the Fronhas water reservoir had, by the time the CORINE Land Cover images for the CLC1990 map were taken, a total area smaller than 25 ha and a width smaller than 100 m, i.e., smaller than the CORINE MMU and the smallest mapped width. As a result, the Fronhas reservoir was not identified in the 1990 map and thus perhaps truly is error consisting of omission of water and commission of forest. Thus, we consider it plausible that commission error at 1990 on 0.003% of the areal extent could account for water appearing to target forest. This 0.003% hypothetical error would account for 5.2% of the apparent transition from forest to water.

Finally, results show that heterogeneous is dormant in terms of gains, though the gain of heterogeneous targets industrial, rainfed and rice. Our understanding of historical processes indicates that heterogeneous category could either emerge from forest if a part of it would be converted to agriculture; or from agriculture if a part of heterogeneous' area was abandoned for natural recovery. Processes of change that can lead to the gain of heterogeneous areas are highly plausible because crop abandonment and crop size reduction were a reality in the Mondego river basin during the period of implementation of severe measures of the European Common Agricultural Policy (CAP) (EC, 2003). Results indicate that omission of heterogeneous error at 2006 on 0.205% of the areal extent could account for the gain of heterogeneous appearing dormant.

4.2. Error Analysis

Büttner et al. (2004) indicate that the error of CLC1990 maps could be close to 15% or even higher. Caetano et al. (2009) registered an error of 9.8% for the Portuguese CLC2006 map. Teixeira et al. (2014) used the same CORINE land-cover maps and registered for the Mondego river basin a total disagreement between 1990 and 2006 of 2.0%. Are the CORINE maps sufficiently accurate such that the temporal differences indicate true deviations from uniform change? The results show that: error on 1.5% of the 1990 map could potentially explain all deviations from uniform losses, error on 2.0% of the 2006 map could potentially explain all deviations from uniform gains, and error on less than 0.7% of the 1990 map could potentially explain all deviations from uniform transitions to each gaining category. These hypothetical errors are smaller than the amount of error we suspect in the maps, in which case map error might be able to explain the apparent deviations from uniform changes. However, we will never be certain whether error explains all deviations from uniform changes. It is easy to imagine how error could explain apparent changes that are inconsistent with supplemental historical information. However, some of the apparent changes are consistent with supplemental information concerning land change history. Thus we do not automatically assume that error accounts for all deviations from uniform changes, because some apparent changes are consistent with our understanding of historical processes.

4.3. CORINE maps as base data

The results give information concerning land cover changes at the category and transition levels using two CLC data layers, the CLC1990 and the CLC2006. The specifications of all CLC products are similar, though some improvements have been made since the CLC1990 (EEA, 2007). Such specifications influence the final map accuracy and interpretation of the results.

Thematic accuracy is the correspondence between the category label assigned by the classification and that observed in ground information. Higher thematic accuracies are expected to positively influence the identification of land cover changes (Feranec et al., 2010). Regarding our case study, the information concerning the CLC1990 accuracy is vague and has probably not achieved the 85% target (Büttner et al., 2004). Our analysis measured the strength of the evidence for the deviations from uniform intensities, in order to shed light on the categories whose errors in the CLC1990 map could account for non-uniform transitions. We found that it is plausible that the error of the CLC1990 map might account for non-uniform transitions from urban to industrial and from water to forest.

The assessment of the thematic accuracy of the CLC2006 has shown an overall accuracy of 90.2% for the Portuguese territory, though some land categories show very low user's and/or producer's accuracies (Caetano et al., 2009). In our study, we assumed that the omission error of heterogeneous at 2006 could account for the gain of heterogeneous appearing dormant. According to Caetano et al. (2009), the omission error at 2006 of the five individual categories that compose the heterogeneous category varies between 48.1% and 12.2%. The high omission errors reported by Caetano et al. (2009) could be negatively influencing the ability to identify land change (Feranec et al., 2010).

Despite the accuracy attained for the CLC maps in terms of both location and attribute (EEA, 2007), a large MMU may lead to misrepresentation of sparse and fragmented land cover categories (Saura, 2002). In the Mondego river basin, forest and heterogeneous are dominant categories, which tend to occupy large continuous patches (Teixeira et al., 2014). On the other hand, urban and industrial areas are sparse and fragmented, especially in the rural areas, which tend to be interspersed with natural and agricultural areas (Mateus, 2009). As a consequence, map generalisation may have led to underestimation (Büttner et al., 2004) of urban and industrial, as well as other less dominant land categories, because isolated patches smaller than 25 ha were not incorporated in the final map. Map generalisation is the most probable explanation for water's gain appearing to target forest.

4.4. Implications for coastal management

The apparent changes that are inconsistent with historical processes are an indication of the misclassification errors that could propagate to other land cover map applications, as in the assessment of processes affecting water supply, demand and quality (Loosvelt et al., 2014). In our case study, results indicate that the apparent transition area from heterogeneous to urban is larger than the apparent transition area from industrial to urban. The three categories affect the hydrological processes of runoff, infiltration and groundwater recharge. Both urban and industrial have very low permeability, while heterogeneous does not. Thus transitions from heterogeneous to urban are expected to have larger effects on water supply than transitions from industrial to urban. Likewise, the three categories affect water quality, but the type of impact expected from each category is different. From urban, we expect an impact on water due to ammonia. From industrial, we expect impacts from ammonia and other chemical contaminants. From heterogeneous, we expect impacts due to nitrate and phosphate.

Coastal and estuarine systems are highly dynamic, with complex interactions and feedback loops. Developing management plans for these areas highly depends on a clear understanding of the problem to be addressed as well as on the degree of certainty (Townend, 2004). The counter-intuitive results concerning urban, industrial and heterogeneous are examples of how a change in perceptions of the problems affecting coastal systems could modify approaches to coastal management.

5. Conclusion

The processes that influence water supply, demand and quality are affected by land change, whose assessment can benefit from the use of Intensity Analysis. Intensity Analysis' approach to compute hypothetical errors provides a structure to evaluate the strength of the evidence for deviations from uniform intensities. Larger hypothetical errors indicate stronger evidence. All apparent deviations from uniform gains could be explained by errors on 2.0% of the 2006 map. All apparent deviations from uniform losses could be explained by errors on 1.5% of the 1990 map. All apparent deviations from uniform transitions to each gaining category could be explained by errors on less than 0.7% of the 1990 map. The map of 1990 is different than the map of 2006 on 2.0% of the areal extent. All of these percentages are lower than the overall error percentage of 9.7±1.3% found for the CLC2006 (Caetano et al., 2009) and lower than the suspected error percentage of 15% for the CLC1990 (Büttner et al., 2004). We analysed the processes of changes that are known to have occurred in our study area in order to interpret whether the hypothetical errors could account for deviations from uniform intensities. We found that some apparent changes are consistent with the supplemental historical record concerning land change processes, in which case errors are not necessarily the reason of the apparent changes. However, errors that confuse urban and industrial might account for the counter-intuitive apparent transitions between urban and industrial. Omission error of heterogeneous at 2006 could account for the empirical observation that the gain of heterogeneous appears dormant. Generalisation procedures for the CLC1990 map might explain the apparent transition from water to forest. The method to quantify hypothetical errors has allowed us to explain counter-intuitive land changes that the raw data indicate but that no known historical processes can explain.

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