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Scenarios and Modeling of Land Use and Cover Changes in Portugal from 1980 to 2040

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ABSTRACT

In this study, land use and cover changes in continental Portugal are analyzed for years 1980, 1995 and 2010 using samples of the Landyn research project. The modeling approach includes testing the hypothesis that land cover changes are generated by a first-order Markov process. Results show that the changes in land use and cover are dependent of the previous moment in time, i.e., they follow a Markov process. Accordingly, multi-decadal land cover projections of Landyn simplified land cover classes are legitimately presented and analyzed for continental Portugal and its regions for years 2020, 2030 and 2040. To make these results spatially explicit, a modelling approach which combines Markov chains with cellular automata is carried out using hypothetical scenarios. The quantitative and spatially explicit information provided by this study enables a better understanding of tendencies in land cover change and may be useful for territorial planning and management.

Keywords: *Cellular Automata, Landyn, LUCC, Markov Chains, Stochastic Model*

INTRODUCTION

Land use and land cover change (LUCC) has been proving itself as an important phenomenon with significant impacts in environment, soil consumption, population health, and life quality. Understanding studying this observable fact can help policy makers and land planners to take better decisions. Even though spatial data infrastructures and users are growing, the application of knowledge to support spatial decisions has not met an equivalent increase (Murgante et al. 2009). Thus, studies to support spatial planning decisions are needed.

Markov chains are one way of analyzing and projecting land cover changes and have been successfully applied in many studies. (Turner 1987) compared the results of a Markov chain

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model with others from spatial simulation models to project land cover changes in Georgia, USA. (Muller and Middleton 1994) used first-order Markov chains to investigate the dynamics of land cover changes in Niagara, Canada, between 1935 and 1981. (Cabral and Zamyatin 2009) evaluated, using remotely sensed Landsat images, the influence of the Natural Park of Sintra-Cascais, in the land cover dynamics of the municipalities of Sintra and Cascais, Portugal, between 1989 and 2001, with Markov chains. (Iacono et al. 2012) used a Markov model with land cover data between 1958 and 2005 to estimate the fraction of available land for transportation in Minneapolis, USA. (Chen et al. 2013) investigated and projected future land cover changes using Markov chains in the mangrove forest of Honduras using Landsat images obtained between 1985 and 2013.

The Markov chains do not predict the changes of land use in a spatially explicit way which may limit the usefulness of the results obtained with these models. One way to overcome this limitation is to combine Markov chains with cellular automata. This combination of models has been used in studies related with LUCC modelling (Ahmed et al. 2013; Kityuttachai et al. 2013; Martins et al. 2012; Pontius JR and Malanson 2005; Tewolde and Cabral 2011).

This study is developed within the Landyn's research project which extends the period of analysis of previous studies of LUCC in continental Portugal back to the 80ies (DGT 2013). Landyn's main objectives are (DGT 2013): (i) to provide a good understanding of the LUCC changes; (ii) to identify and understand the major driving forces of changes; (iii) to use a spatial model to build alternative scenarios of LUCC and; (iv) to study energy demand and Greenhouse Gases (GHG) emissions and removals.

In this paper, we report the results of the third objective of Landyn project. We start by investigating whether the LUCC in continental Portugal depend on the changes occurred in the previous time moment. If this hypothesis is proved, then the projection for future land cover using Markov chains is legitimate, considering that the past land change matrixes are stationary in time. Subsequently, a spatial model based on these land change matrixes is developed with cellular automata (CA) to reflect hypothetical scenarios of LUCC in the study area.

DATA AND METHODS

Data

The Landyn project covers continental Portugal (Figure 1). Random sample units based on the Eurostat guidelines – Land Use and cover Area Frame Survey (LUCAS), corresponding to 499596 ha, approximately 6% of the territory, were created for the years of 1980, 1995 and 2010. The dataset, comprising 1279 samples, was made available by the Portuguese Territory General Directorate (DGT). This was composed by 2x2 elements of the reference grid, i.e., elements with 4 km2 (DGT 2013). In the sample grid, a reference grid of 1x1 km2 (ETRS89-LAEA 52N 10E) of the European Environmental Agency was adopted (DGT 2013).

The Landyn classification scheme is composed of 32 classes (Table 1). For the sake of simplicity, in this study are only analyzed and reported the results for the 7 simplified classes.

Data Preprocessing and Transition Matrixes Calculation

The samples dataset in ESRI shapefile format ("ArcGIS" 2013) were converted into a raster format (tiff) with a 100-meter spatial resolution and then imported into the IDRISI Selva software (Clark Labs, 2013). The transition matrixes for the periods of 1980-1995, 1995-2010 and 1980-2010 were calculated.

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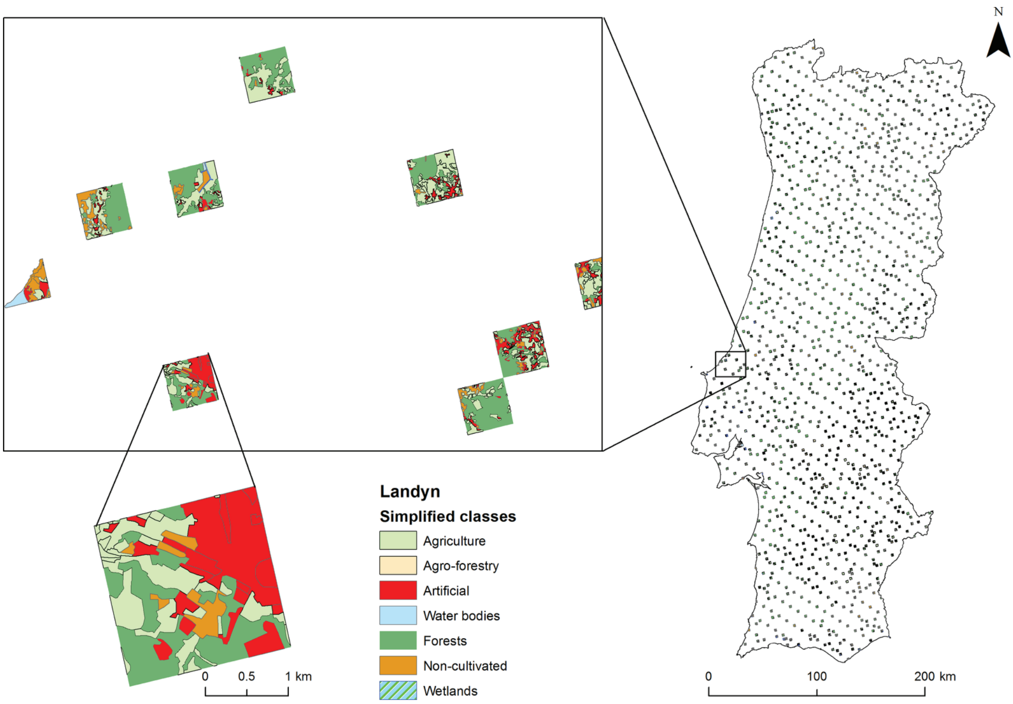
Figure 1. Study area and Landyn samples



Markov Chains

Stochastic processes generate sequences of random variables {Xn, n T} by probabilistic laws. In this study, index n represents time. The process is considered discrete in time and T = {0, 5, 10 …} years approximately, which is a reasonable time unit for studying LUCC phenomenon. If the stochastic process is a Markov process, then the sequence of random variables will be generated by the Markov property (1), formally:

$$P[X_{n+1}=a_{in+1} \mid X_0=a_{i0}, ..., X_{in}=a_{in}] = P[X_{in+1}=a_{in+1} \mid X_{in}=a_{in}] \tag{1}$$

where $n \in T$ and T = {0, 5, 10,…} and i the range of possible values that a_i can assume, in this case the 7 simplified classes defined previously. When the range of possible values for a_i is either finite or infinite denumerable, as in this study, the Markov process may be referred as a Markov chain. To demonstrate that LUCC in the study area is a Markovian process, one must prove that: (i) there is a statistical dependence between X_{n+1} and X_n (2); and, (ii) that the statistical dependence is a first-order Markov process (3):

$$P(X_n=a_n \mid X_{n-1}=a_{n-1}) \neq P(X_n=a_n) * P(X_{n-1}=a_{n-1}) \tag{2}$$

$$P[X_n=a_n \mid X_{n-1}=a_{n-1}] = P[X_n=a_n, X_{n-1}=a_{n-1}] / P[X_{n-1}=a_{n-1}] \tag{3}$$

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Table 1. Landyn classes

Simplified Classes	Landyn Classes	
Agriculture	L10	Non-irrigated arable land
	L11	Permanently irrigated land
	L12	Rice fields
	L13	Vineyards
	L14	Orchards
	L15	Olive groves
	L16	Permanent pastures
	L17	Complex cultivation patterns
Agro-forestry	L18	Agro-forestry systems
Artificial	L1	Continuous urban fabric
	L2	Non-continuous urban fabric
	L3	Industrial, commercial and general units
	L4	Road and rail networks and associated land
	L5	Port areas
	L6	Airports
	L7	Mineral extraction sites
	L8	Dump areas
	L9	Construction sites
	L32	Golf courses
Water bodies	L31	Water bodies
Forest	L19	Broad-leave forest (excluding eucalyptus and invasive species)
	L20	Coniferous forest
	L21	Eucalyptus and invasive species
	L24	Other woody formations; cuts and new plantations, forest nurseries, Fire lines and / or firebreaks
	L27	Open broad-leave forest (excluding eucalyptus and invasive species)
	L28	Open coniferous forest
	L29	Open forest of Eucalyptus and invasive species
Non-cultivated	L22	Herbaceous natural vegetation
	L23	Scrubland
	L25	Open spaces with little or no vegetation
	L26	Burnt areas
Wetlands	L30	Wetlands

A first-order Markov process is a Markov process where the transition from a class to any other does not require intermediate transitions to other states. The statistical dependence can be tested as in any contingency table (Murteira 1990) displaying the land use/cover change between X_n and X_{n-1}. In our study, this test is performed for the LUCC between 1995 and 2010. To infer

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from the association or independence between the land use/cover classes in different years from the contingency table, the random variable, with the chi-square distribution will be defined by (4):

$$\chi^2 = \sum_i \sum_j \left(\left(N_{ij} - M_{ij} \right)^2 / M_{ij} \right) \tag{4}$$

where N will be the contingency matrix displaying the LUCC between 1994 and 2000, and M the contingency matrix with the expected values of change assuming the independence hypotheses (Murteira 1990).

χ^2 measures the distance between the observed values of LUCC and the expected ones assuming independence and must be high enough to prove (2), for $(7\text{-}1)^2$ degrees of freedom. The same non-parametric test will be used to test the Markov property. In this case, the values to be compared with the observed ones will be calculated from the Chapman-Kolmogorov Equation (5) (Kijima 1997), assuming that these variables are generated by a first-order Markov process:

$$P(X_n{=}a_n \mid X_m{=}a_m) = P(X_l{=}a_l \mid X_m{=}a_m)\, P(X_n{=}a_n \mid X_l{=}a_l),\ m \le l \le n \tag{5}$$

The Chapman-Kolmogorov equation states that transition probabilities from years 1980 to 2010 can be calculated by multiplying the transition probabilities matrix from years 1980 to 1995 by the transition probabilities matrix from years 1995 to 2010.

Cellular Automata with Markov Model

The spatial component of the modelling process was carried using CA combined with Markov chains through the CA_Markov module implemented in IDRISI software. CA are dynamic models which are discrete in time, space and state (Balzter et al. 1998; Deep and Saklani 2014). In CA_Markov, the change of cell's classes is modelled using a Markov transition matrix, a suitability map and a neighborhood filter (Eastman 2012).

In this study, the transition matrix and the number of cells changing class was obtained using 1990 and 2000 CLC maps in the Markov module available in IDRISI. The transition suitability image collection was created using only the transition conditional probabilities without considering other constraints and/or factors. The selected neighborhood filter was a 5x5 cell window.

Spatial Explicit Scenarios for Year 2040

The modelling scenarios can be based on narratives incorporating likely future changes in important drivers (Raskin 2005). These can be built using a participatory approach with the stakeholders or concept-driven (Castella 2005; Guerry et al. 2012; Walz et al. 2007).

In this study, we implement a concept-driven scenario building approach aimed to engage initial discussion with policy-makers and land-use planners. Three alternative scenarios are proposed for year 2040 reflecting different LUCC policies: (1) environmental sustainability; (2) Gross Domestic Product (GDP); and (3) desertification. The scenarios are built changing the transition areas file of the transition matrixes. Finally, changes in BAU and in the scenarios are obtained using the prediction for 2010 as reference.

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RESULTS

Land Use and Cover Changes

As described in the methodology, the main hypothesis to be tested in this study (H_0) is that LUCC in the study area is generated by a first order Markov process. To prove H_0, two subsidiary hypotheses must be verified: (i) H_1 - land use/cover in different time periods is not statistically independent, and (ii) H_2- LUCC in the study area is a Markov process.

To evaluate the changes in land use and cover in the study area, several contingency tables were calculated for the periods of 1980-1995, 1995-2010 e 1980-2010 (Tables 2, 3, and 5).

The quantities of land change are quite similar for both time periods (12.49% in 1980-1995 and 12.9% in 1995- 2010). From 1980 to 1995, the "forest" class lost 8% of its area to the "non-cultivated" class being also remarkable the loss of agriculture land for cultivated land (4% of the total area of "agriculture") and forest (4% of the total area of "agriculture"). From 1995 to 2010, there was an increase in the "water bodies" class due to the construction of new dams (29.3%). Between 1995 and 2010, there was an important change from "non-cultivated" class to "forest" (17% of the "non-cultivated" total area). It is also remarkable the loss of agriculture land (-7.7%) in this period. Between 1980 and 2010, there was a significant transition of land use and land cover from "agriculture" to "forest" (9% of total area of "agriculture") and from

Table 2. Contingency table 1980-1995 (AG:Agriculture; AF:Agroforestry; A:Artificial; WB:Water bodies; F:Forests; NC:Non-cultivated; W:Wetlands)

		1980									
		AG	**AF**	**A**	**WB**	**F**	**NC**	**W**	**T**	**Δha**	**Δ%**
1995	**AG**	181148	1889	177	67	2581	3526	2	189390	-10534	-5.3
	AF	478	42582	0	0	2864	119	0	46043	-4015	-8.0
	A	2324	61	14844	7	1152	715	7	19110	3917	25.8
	WB	94	59	8	4288	32	92	0	4573	81	1.8
	F	7781	4908	79	30	137478	11447	0	161723	4592	2.9
	NC	8095	559	84	98	13003	55770	12	77621	5909	8.2
	W	4	0	1	2	21	43	1065	1136	50	4.6
	T	199924	50058	15193	4492	157131	71712	1086	499596	62421	**12.49**

Table 3. Contingency table 1995-2010 (AG:Agriculture; AF:Agroforestry; A:Artificial; WB:Water bodies; F:Forests; NC:Non-cultivated; W:Wetlands)

		1995									
		AG	**AF**	**A**	**WB**	**F**	**NC**	**W**	**T**	**Δha**	**Δ %**
2010	**AG**	166907	1638	65	3	2591	3687	0	174891	-14499	-7.7
	AF	856	40018	0	3	2738	254	0	43869	-2174	-4.7
	A	2788	69	18853	18	1782	1267	3	24780	5670	29.7
	WB	668	400	18	4483	244	101	0	5914	1341	29.3
	F	10657	3662	108	10	144981	13532	6	172956	11233	6.9
	NC	7501	256	66	56	9387	58780	4	76050	-1571	-2.0
	W	13	0	0	0	0	0	1123	1136	0	0.0
	T	189390	46043	19110	4573	161723	77621	1136	499596	64451	12.90

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"non-cultivated" to "forest" (24.2% of total area of "non-cultivated". The "artificial" class was the one that increased most in this period (63.1%).

Multi-Decadal Projection of Land Use and Land Cover for Continental Portugal with Markov Chains

The χ^2 obtained to measure the association between the contingency table of 1980-2010 (Table 4) and the Chapman-Kolmogorov equation is 0.3223. This value is clearly below the critical value of the distribution for a significance level of 0.950 which is 17.887 for (7-1)^2 $\left(7-1\right)^2$ degrees of freedom. This result allows the assumption that LUCC is a Markovian process in the study area. Based on these values, projections of land use and land cover for years 2020, 2030 and 2040 were made using the transition matrix 1995-2010 (Figure 2) (*Takada et al. 2009*). The most recent transition matrix was used because it is the one expected to produce more reliable results (*Iacono et al. 2012*).

The proportion of the area occupied by the "agriculture" class will significantly decrease until 2040. The projection indicates that this class will represent only 30.1% of the territory when, in 1980, it represented 39.3%. This decrease is made mainly due to the significant increase of the "artificial" and "forest" classes. We note a slightly, yet consistent, decrease of the "agro-forestry" class between 1980 and 2040. The values, in ha, of the 2040 projection are presented in Table 5. In this table, the tendency of previous years is repeated between 2010 and 2040, mainly for the "artificial" and "water bodies" classes, respectively, 43.5% and 41.6%.

Analysis for NUTS 2 Level in the Period of 1980-2040

The same method was applied individually for each of the 5 NUTS 2 region of Portugal. All the 5 regions exhibited a Markovian behavior on the LULC change between 1980 and 2010. In Table 6, are presented the values obtained for the χ^2 in each region, all of them below the critical value of the distribution for a significance level of 0.950 which is 17.887 for (7-1)^2 $\left(7-1\right)^2$ degrees of freedom

In Figure 3 are presented the historic and future tendencies of LUCC of each NUTS 2 region of Portugal.

Table 4. Contingency table 1980-2010 (AG:Agriculture; AF:Agroforestry; A:Artificial; WB:Water bodies; F:Forests; NC:Non-cultivated; W:Wetlands)

		1980									
		AG	**AF**	**A**	**WB**	**F**	**NC**	**W**	**T**	**Δha**	**Δ %**
2010	**AG**	162067	3410	157	46	4312	4899	0	174891	-25033	-12.5
	AF	1198	38311	0	0	4141	219	0	43869	-6189	-12.4
	A	5203	145	14825	15	3004	1580	8	24780	9587	63.1
	WB	751	461	15	4265	253	169	0	5914	1422	31.7
	F	18114	7178	106	39	130196	17323	0	172956	15825	10.1
	NC	12574	553	90	126	15210	47480	17	76050	4338	6.0
	W	17	0	0	1	15	42	1061	1136	50	4.6
	T	199924	50058	15193	4492	157131	71712	1086	499596	101391	**20.3**

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Table 5. Contingency table 1980-2040 (AG:Agriculture; AF:Agroforestry; A:Artificial; WB:Water bodies; F:Forests; NC:Non-cultivated; W:Wetlands)

		2010									
		AG	**AF**	**A**	**WB**	**F**	**NC**	**W**	**T**	**Δha**	**Δ %**
2040	**AG**	136356	2800	164	11	5514	6145	0	150990	-23901	-13.7
	AF	1573	33206	3	8	5216	646	0	40652	-3217	-7.3
	A	5034	189	24122	47	3799	2365	6	35562	10782	43.5
	WB	1182	716	47	5683	540	208	0	8376	2462	41.6
	F	18782	6292	283	38	141149	22156	12	188712	15756	9.1
	NC	11942	666	161	127	16738	44530	7	74171	-1879	-2.5
	W	22	0	0	0	0	0	1111	1133	-3	-0.3
	T	174891	43869	24780	5914	172956	76050	1136	499596	113439	**22.7**

Figure 2. Tendency of land use and land cover distribution in the period 1980-2040

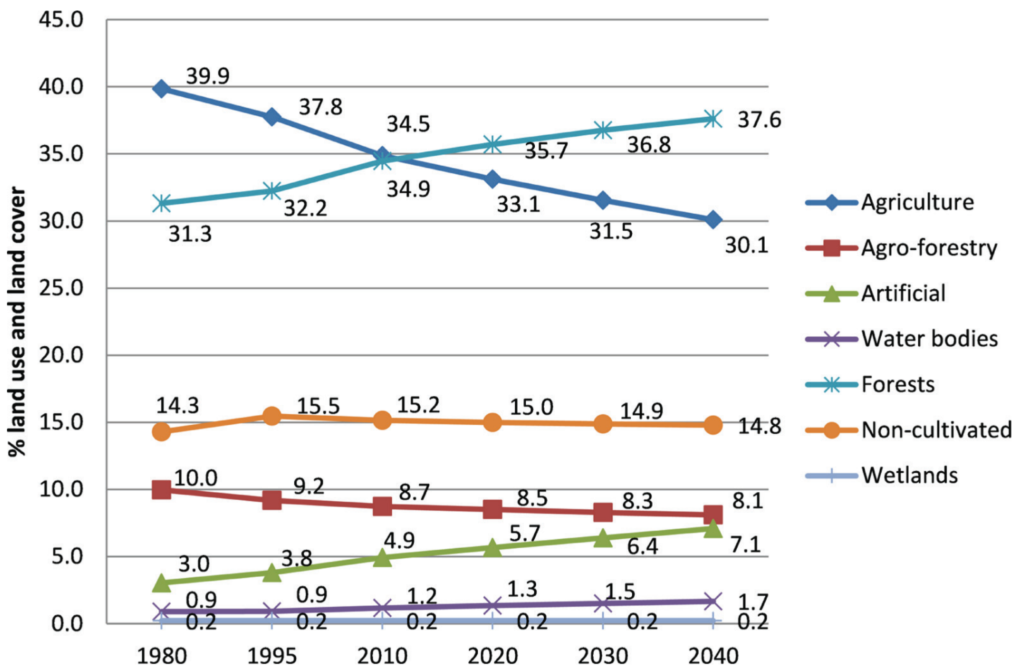

Table 6. Chi-square values for the NUTS 2 regions of Portugal

Region	χ^2
Norte	3.828
Centro	7.208
Lisboa	2.851
Alentejo	1.662
Algarve	2.514

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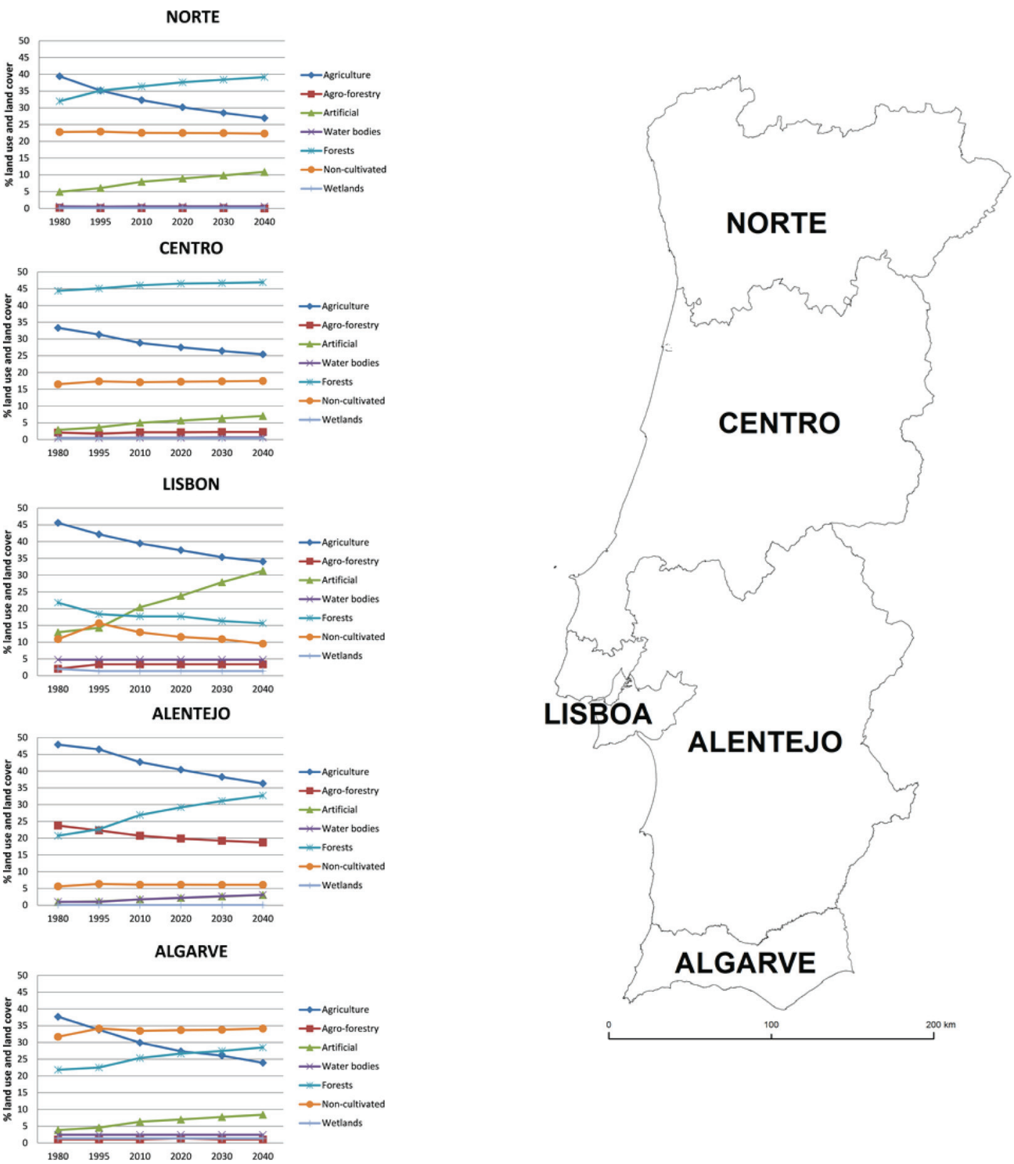
Figure 3 provides a good picture of Portugal's NUTS 2 region's heterogeneity regarding the land use and land cover proportion and the tendencies of change (past and future). In 2040, 31.3% of land use and land cover in Lisboa region will be artificial. This represents an enormous increase when compared to 1980 when this class occupied only 12.9% of the total area of this region. The artificial areas are increasing in all regions. The decrease in the agriculture class is common for the 5 regions. Lisboa is the only region where the forests are decreasing in this time period.

Figure 3. Historic and future tendencies of LUCC of each NUTS 2 region of Portugal



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Spatial Explicit Projection of Land Use and Cover with Cellular Automata and Markov Chains

The spatial projection of land use and cover was carried out with CA_Markov module available in IDRISI software. The 1990-2000 transition matrix (obtained using the CLC maps), the suitability maps for each of the 7 classes (corresponding to the resulting transition conditional probabilities) and a Moore neighborhood filter (5x5 cell) were the components used as input in this tool to project land use and cover to year 2010. From this operation it was possible to define the change location based on the number of cells that must be used on each transition (Araya, Cabral 2010).

The estimated result for 2010 was compared with real map of 2010 that matches the sample units for 2010 decade using quantity and allocation disagreement measures (*Pontius and Millones 2011*). The values obtained were, respectively, 9.7% and 22.4%. These values are similar to the null value (i.e. a model of no change) for the quantity disagreement and slightly higher for the allocation disagreement (21.9%).

The projection of land use and cover was calculated for year 2040 resulting in the BAU map for year 2040 (Figure 4).

Scenarios for 2040

The 3 alternative scenarios were built changing the number of cells expected for each class in year 2040. Using these estimates, the proportions of land use and cover for each scenario were obtained after running the model with the same transition conditional probabilities and with the same suitability map that were used for simulating the map of 2010, now with 40 iterations (Table 7 and Figure 5).

The created scenarios translate hypothetical development strategies whereas the BAU corresponds to a situation in which estimated LUCC for 2040 results from the same transitions verified between 1990 and 2000 (Figure 6). For instances, in the environmental sustainability scenario there will be an increase in the forest class (+28.3%) and a decrease in the agriculture (-18.2%) and in the non-cultivated classes (-51.7%) when compared to 2010. In the GDP scenario there will be an increase of the agriculture (+14.3%), agroforestry (+19.1%) and in the artificial classes (+81.6%). In this scenario the forest class decreases about 19.3%. Finally, in the desertification scenario, there will be an increase in the non-cultivated (+479.9%) and in the artificial (+147.7%) classes. For this scenario is projected a decrease in the agriculture (-27.1%) and in the agroforestry (-83.4%) classes.

CONCLUSION

This work used samples of land use and land cover of the Landyn project for the years of 1980, 1995 and 2010. We found that the LUCC followed a Markovian behavior during this period in the study area. LUCC projections are, thus, legitimate if these changes are stationary in time. The obtained results can be extrapolated for the total study area within the limits of confidence of the sampling method.

One important limitation of Markov chains modeling is the absence of spatial explicit land use and cover projections. To overcome this limitation, a spatially explicit model was implemented with cellular automata. A spatial projection was made for year 2040 reflecting a similar transition mechanism of land use and cover change to the one verified between 1990 and 2000 (i.e. business as usual).

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Figure 4. Estimated land use and cover for year 2040

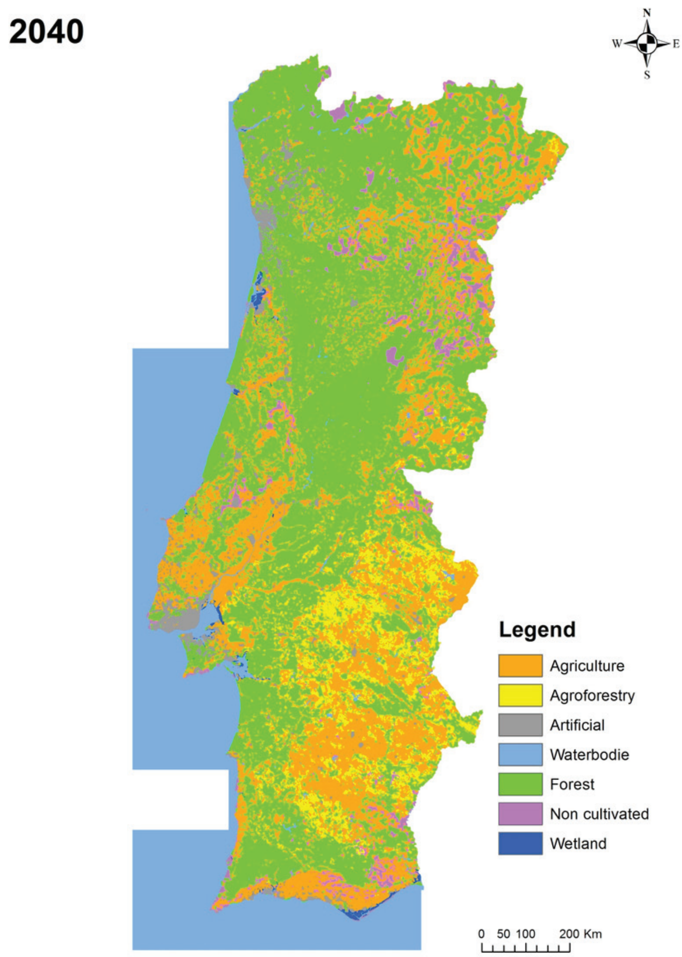

Table 7. Expected % of land use and land cover for 2040 in BAU and for each scenario (AG:Agriculture; AF:Agroforestry; A:Artificial; WB:Water bodies; F:Forests; NC:Non-cultivated; W:Wetlands)

Classes	BAU	Environmental Sustainability	GDP	Desertification
AG	29.5	25.7	35.8	27.1
AF	5.4	5.0	6.5	2.7
A	4.9	4.0	5.6	6.8
WB	22.2	22.4	22.2	22.5
F	32.5	39.4	24.8	31.7
NC	5.2	3.3	4.8	8.8
W	0.2	0.3	0.2	0.2

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Figure 5. Scenarios of land use and cover for year 2040

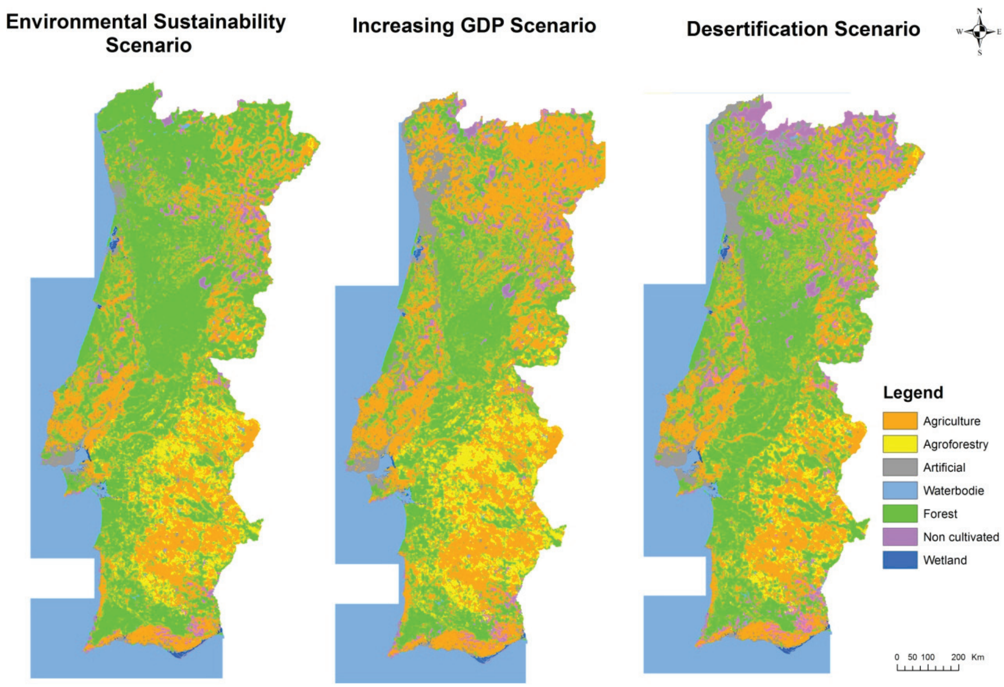
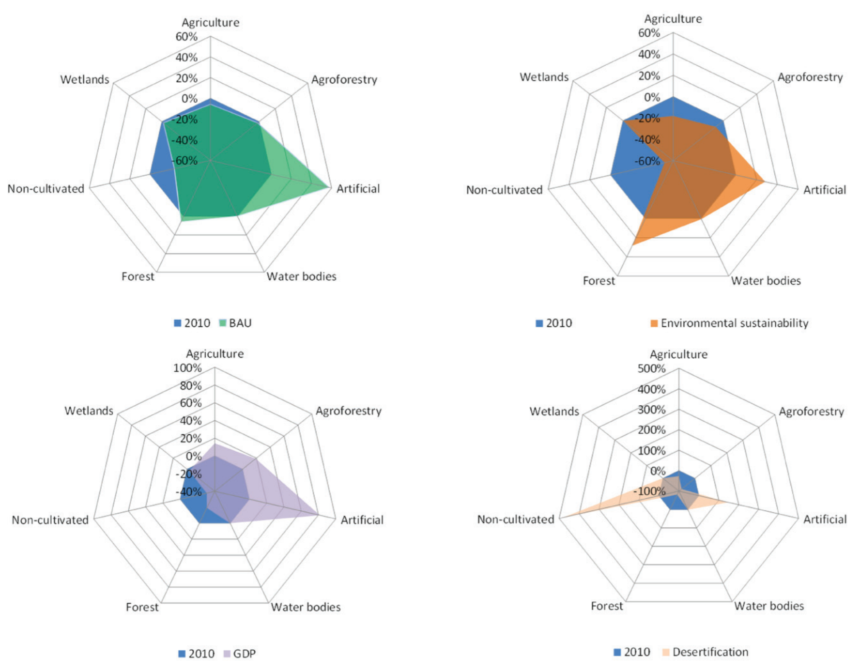


Figure 6. Scenarios of land use and cover for year 2040 compared with the reference year of 2010



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The hypothesized scenarios of land use and cover strategies for year 2040 revealed to be a powerful tool for understanding the existing tradeoffs between the several scenarios, for communicating results and to engage discussions with land use planners. These scenarios can be easily adapted to reflect different strategies.

Nevertheless, some limitations of this type of modelling approach need to be considered. The use of transition matrixes over a time period can lead to wrong short-term projections or without spatial continuity. Additionally to the spatial proximity of land use and cover, important drivers of change such as cyclic economic factors, specific development policies, natural catastrophes, new infrastructures such as the Alqueva dam, which were not considered in the study may compromise the stationary element required for the success of this type of modeling. Other factors, such as proximity to roads, slope, aspect, and others would likely have a positive impact the predictive power of the model. However, due to the long time spam covered by this study, it was not possible to find suitable data for the whole time period (e.g., roads).

The combination of Markov chains with CA successfully provided quantitative and spatially explicit information enabling a better understanding of future tendencies in land cover change in Portugal. These results may be useful for territorial planning and management.

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REFERENCES

Ahmed, B., Ahmed, R., and Zhu, X. 2013. "Evaluation of Model Validation Techniques in Land Cover Dynamics," *ISPRS International Journal of Geo-Information* (2:3), pp. 577–597 (doi:).10.3390/ijgi2030577

ArcGIS.," 2013., ESRI (available at http://www.esri.com/software/arcgis)

Balzter, H., Braun, P. W., and Köhler, W. 1998. "Cellular automata models for vegetation dynamics," *Ecological Modelling* (107:2-3), pp. 113–125 (doi:).10.1016/S0304-3800(97)00202-0

Cabral, P., and Zamyatin, A. 2009. "Markov Processes in Modeling Land Use and Land Cover Changes in Sintra-Cascais, Portugal," *Dyna-Colombia* (76:158), pp. 191–198.

Castella, J.-C. 2005. *Participatory simulation of land-use changes in the northern mountains of Vietnam: the combined use of an agent-based model, a role-playing game, and a geographic information system*.

Chen, C.-F., Son, N.-T., Chang, N.-B., Chen, C.-R., Chang, L.-Y., Valdez, M., Centeno, G., Thompson, C., and Aceituno, J. 2013. "Multi-Decadal Mangrove Forest Change Detection and Prediction in Honduras, Central America, with Landsat Imagery and a Markov Chain Model," *Remote Sensing* (5:12), pp. 6408–6426 (doi:).10.3390/rs5126408

Clark Labs. 2013. "IDRISI," (available at http://www.clarklabs.org/products/idrisi.cfm)

Deep, S., and Saklani, A. 2014. "Urban sprawl modeling using cellular automata," *The Egyptian Journal of Remote Sensing and Space Science* (17:2), pp. 179–187 (doi:).10.1016/j.ejrs.2014.07.001

DGT. 2013. "LANDYN – Alterações de uso e ocupação do solo em Portugal Continental: caracterização, forças motrizes e cenários futuros," *Relatório Anual 2012-2013*, Direção-Geral do Território, Lisboa (available at http://landyn.isegi.unl.pt/reports/)

Eastman, R. (2012). *Idrisi Selva*. Clark Labs.

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Guerry, A. D., Ruckelshaus, M. H., Arkema, K. K., Bernhardt, J. R., Guannel, G., Kim, C.-K., Marsik, M., Papenfus, M., Toft, J. E., Verutes, G., Wood, S. A., Beck, M., Chan, F., Chan, K. M. A., Gelfenbaum, G., Gold, B. D., Halpern, B. S., Labiosa, W. B., Lester, S. E., Levin, P. S., McField, M., Pinsky, M. L., Plummer, M., Polasky, S., Ruggiero, P., Sutherland, D. A., Tallis, H., Day, A., and Spencer, J. 2012. "Modeling benefits from nature: using ecosystem services to inform coastal and marine spatial planning," *International Journal of Biodiversity Science, Ecosystem Services & Management* (8:1-2), pp. 107–121 (doi:).10.1080/21513732.2011.647835

Iacono, M., Levinson, D., El-Geneidy, A., & Wasfi, R. 2012. "Markov Chain Model of Land Use Change in the Twin Cities," University of Minnesota: Nexus Research Group (available at http://ideas.repec.org/p/nex/wpaper/markovlu.html)

Kijima, M. (1997). *Markov processes for stochastic modeling Stochastic Modeling Series*. London: Chapman & Hall. doi:10.1007/978-1-4899-3132-0

Kityuttachai, K., Tripathi, N., Tipdecho, T., and Shrestha, R. 2013. "CA-Markov Analysis of Constrained Coastal Urban Growth Modeling: Hua Hin Seaside City, Thailand," *Sustainability* (5:4), pp. 1480–1500 (doi:).10.3390/su5041480

Martins, V. N., Pires, R., and Cabral, P. 2012. "Modelling of coastal vulnerability in the stretch between the beaches of Porto de Mós and Falésia, Algarve (Portugal)," *Journal of Coastal Conservation* (16:4), pp. 503–510.

Muller, M., and Middleton, J. 1994. "A Markov Model of Land-Use Change Dynamics in the Niagara Region, Ontario, Canada," *Landscape Ecology* (9:2), pp. 151–157.

Murgante, B., Borruso, G., & Lapucci, A. 2009. "Geocomputation and Urban Planning 2 Geocomputational Applications in Urban Planning," (Longley 1998), pp. 1–17. doi:10.1007/978-3-540-89930-3

Murteira, B. (1990). *Probabilidades e estatística* (2nd ed., Vol. II). McGraw-Hill.

Pontius JR, R. G., and Malanson, J. 2005. "Comparison of the structure and accuracy of two land change models," *International Journal of Geographical Information Science* (19:6), pp. 745–748 (doi:).10.1080/13658810512331389445

Pontius, R. G., and Millones, M. 2011. "Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment," *International Journal of Remote Sensing* (32:15), pp. 4407–4429 (doi:).10.1080/01431161.2011.552923

Raskin, P. D. 2005. "Global Scenarios: Background Review for the Millennium Ecosystem Assessment," *Ecosystems* (8:2), pp. 133–142 (doi:).10.1007/s10021-004-0074-2

Takada, T., Miyamoto, A., and Hasegawa, S. F. 2009. "Derivation of a yearly transition probability matrix for land-use dynamics and its applications," *Landscape Ecology* (25:4), pp. 561–572 (doi:).10.1007/s10980-009-9433-x

Tewolde, M. G., and Cabral, P. 2011. "Urban Sprawl Analysis and Modeling in Asmara, Eritrea," *Remote Sensing* (3:12), pp. 2148–2165 (doi:).10.3390/rs3102148

Turner, M. G. 1987. "Spatial simulation of landscape changes in Georgia: A comparison of 3 transition models," *Landscape Ecology* (1:1), pp. 29–36 (doi:).10.1007/BF02275263

Walz, A., Lardelli, C., Behrendt, H., Grêt-Regamey, A., Lundström, C., Kytzia, S., and Bebi, P. 2007. "Participatory scenario analysis for integrated regional modelling," *Landscape and Urban Planning* (81:1–2), pp. 114–131 (doi:).10.1016/j.landurbplan.2006.11.001

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