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Evaluating the Spatial Uncertainty of Future Land Abandonment in a Mountain Valley (Vicdessos, Pyrenees - France): Insights from Model Parameterization and Experiments

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Abstract: European mountains are particularly sensitive to climatic disruptions and land use changes. The latter leads to high rates of natural reforestation over the last 50 years. Faced with the challenge of predicting possible impacts on ecosystem services, LUCC models offer new opportunities for land managers to adapt or mitigate their strategies. Assessing the spatial uncertainty of future LUCC is crucial for the definition of sustainable land use strategies. However, the sources of uncertainty may differ, including the input parameters, the model itself, and the wide range of possible futures. The aim of this paper is to propose a method to assess the probability of occurrence of future LUCC that combines the inherent uncertainty of model parameterization and the ensemble uncertainty of the future based scenarios. For this purpose, we used the Land Change Modeler tool to simulate future LUCC on a study site located in the Pyrenees Mountains (France) and two scenarios illustrating two land use strategies. The model was parameterized with the same driving factors used for its calibration. The definition of 'static vs. dynamic' and 'quantitative vs. qualitative (discretized)' driving factors, and their combination resulted in four parameterizations. The combination of model outcomes produced maps of the spatial uncertainty of future LUCC. This work involves adapting the definition of spatial uncertainty in the literature to future-based LUCC studies. It goes beyond the uncertainty of simulation models by integrating the uncertainty of the future to provide maps to help decision makers and land managers.

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Introduction

Land and natural resources management requires extensive analysis of possible future LUCC in order to better adapt and mitigate actions (Mitchley et al. 2006). Even if the future is uncertain and different futures are possible, exploring what might happen helps to identify areas at stake by assessing the influence of various land use dynamics and land management strategies (Houet et al. 2010). In the last two decades, many LUCC models have been developed to better understand, assess and project future LUCC as part of land change science (Turner et al. 2007). The use of spatially explicit models to project and explore alternate LUCC futures has become a popular approach in land change research (Veldkamp and Lambin 2001). However, LUCC models include a large range of methodological approaches and choosing the right one is decisive in a forecasting study (Gaucherel and Houet 2009). Although a model is usually selected according to a specific objective, e.g. reproducing landscape patterns (pattern-based models) or simulating spatial processes of LUCC (process-based models), selection primarily depends on the spatial extent of the study area (Houet 2015). Process-based models are widely used in micro-scale studies since they incorporate both social and physical dynamics to identify emerging phenomena through interactions and feedback (Dearing et al. 2010). Pattern-based models are more common in LUCC studies at larger spatial scales and are used to predict whether past trends of change will continue in the future, while taking "natural" land cover dynamics into account (Verburg et al. 2006). However, no perfect model for simulating LUCC exists (Mas et al. 2014) and all the output projections are subject to uncertainty (Messina et al. 2008; Batisani and Yarnal 2008). The challenges of LUCC models are associated with errors and uncertainty assessment (Messina et al 2008). Uncertainty in LUCC models originates from various sources. Part of the uncertainty is inherent to the data and knowledge integrated in the model, i.e. *production-oriented uncertainty* as defined by Leyk et al. (2005). Another part is caused by data processing and simulation, i.e. the interactions between multiple social and biophysical variables. This is the *transformation-oriented uncertainty* (Leyk et al. 2005). To assess the influence of each variable or of a combination of variables, uncertainty and sensitivity analyses can be conducted (Batisani and Yarnal 2008). Uncertainty analysis is the determination of the improbability of the model output emanating from a given model input and parameterization, while sensitivity analysis is the determination of the contribution of individual inputs to model output uncertainty (Helton 2006). Another source of uncertainty can also be considered when using LUCC models, which does not depend on either inputs or on the model: the uncertainty of the future. Exploring different possible futures combining scenarios and LUCC models can help reduce the future uncertainty (Godet 1986; Houet et al. 2010) of possible and (un) desirable LUCC.

The aim of this paper is to assess the spatial uncertainty of future LUCC, and the question we will try to answer is "Is one particular location more likely to change in the future than another?". Given the different sources of uncertainty (i.e. concerning possible futures, models, and parameters), we propose a method adapted from the multi-model ensemble approach (Peng et al. 2002). For the purpose of this demonstration, we apply the method using only two scenarios, with four sets of parameters for each scenario, and a single simulation tool. The aim is to provide uncertainty maps of future LUCC that account for the sensitivity of model parameterization and multiple LUCC scenarios to pinpoint the areas expected to be concerned by specific land changes. Such maps should be helpful for land management. Our main assumptions in this study are: (1) the way input variables are represented (qualitative vs. quantitative) influences the ability of the model to simulate landscape patterns; (2) while model parameterization is expected to have a significant impact on model outcomes, the use of dynamic variables rather than static variables should help improve LUCC allocation; (3) future scenarios are equiprobable (but can be modified and/or evaluated throughout participatory approaches). Accordingly, we perform uncertainty analysis (Crosetto et al. 2000) to identify and evaluate the confidence intervals inherited from model parameterization and future scenarios. This method adapts the definition of spatial uncertainty (Ligman-Zielinska and Jankowski 2014; Tenerelli and Carver 2012) to future based LUCC studies.

Application is made on a mountain landscape located in the southern Europe where land managers face great challenges. Indeed, over the past 50 years, major Land Use and Cover Changes (LUCC) have taken place there. These changes are expected to intensify, thus obliging many European regions to face demographic, economic, organizational and technological modifications (MacDonald et al. 2000, European Commission, 2004). Many authors have confirmed that the expected changes will be rapid and predict massive natural reforestation at the expense of agricultural land (Rounsevell et al. 2005; Verburg et al. 2010). The increasing need to monitor and simulate future LUCC stems from the environmental and sociological stakes that mountainous areas represent. European mountainous areas have experienced significant climatic disruptions (Diaz and Bradley 1997) and will be subject to increased precipitation in addition to a global rise in temperature in the coming decades (López-Moreno et al. 2008). Mountain ecosystems are highly sensitive to climate variability since annual climate variations influence natural reforestation near or beyond the tree line (Batllori and Gutiérrez 2008, Peringer et al. 2013). Forest expansion is also affected by land use changes such as reduced pressure from livestock and abandonment of farm holdings (Julien et al. 2006; Gibon et al. 2010). Mountainous areas are particularly sensitive to these climate and anthropogenic changes as they depend to a great extent on socio-economic factors (Rutherford et al. 2008). Indeed, most mountainous landscapes have been influenced by human activities (Gellrich et al. 2007; Dale 1997) for periods exceeding centuries, and even millennia in Europe (Galop et al. 2011; Galop et al. 2013). Most spatially explicit studies of LUCC in mountain landscapes based on remote sensing data (for e.g. Cohen et al 2011; Bucala 2014) highlight the close correlation between land abandonment and natural reforestation since the 1950s. Although reforestation can have positive outcomes (e.g. carbon storage, soil restoration, etc.) it can also have a lasting effect on environmental aspects including biodiversity (Laiolo et al. 2004), water supply (Szczypta et al. 2015), landscape attractiveness (Mottet et al. 2006), and fire hazards (Curt et al. 1998). In addition, the expansion of forest on formerly open land is often perceived by local users as a cultural loss tied to traditional activities (Hochtl et al. 2005). Overall, land abandonment is a threat to the support of mountain agro-pastoralism since encroachment and reforestation usually leads to a decrease in forage quality and requires significant financial resources to restore pastures to their original state. Local LUCC processes are thus an important part of global environmental changes that affect not only present biodiversity but also ecosystem services (Rounsevell et al. 2006; Lambin and Geist 2006).

1 Methods

1.1 Overall methodological approach

Figure 1 describes the overall methodological approach and the sections in which methodological details are given. The main principle consists in using GIS input maps into a LUCC model to calibrate it using LUCC maps and multiple qualitative and/or quantitative drivers. Once calibrated, it simulates future LUCC based on two scenarios. The combination of the simulated output maps will provide the future spatial uncertainty map.

1.2 Study site and observed past landscape changes

The Vicdessos valley is located in the Department of Ariège in the French Pyrenees (Figure 2). The study site is an Observatory of Human-Nature interactions supported by the CNRS (French National Center for Scientific Research). The study area covers 176.5 square kilometers. LUCC were monitored since the 1940s at a decadal temporal resolution (only some

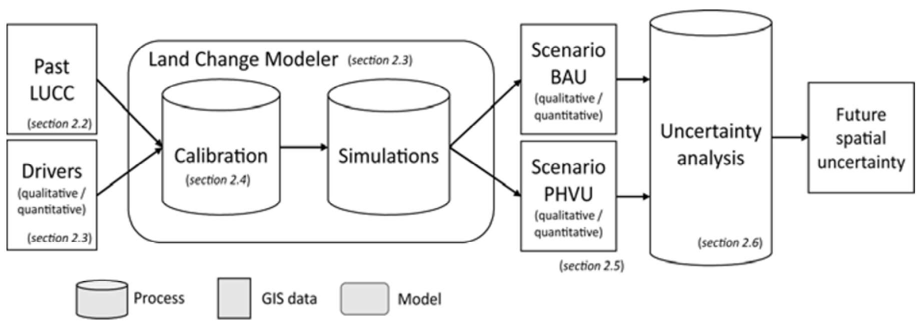

Figure 1 Overview of the general methodological approach.

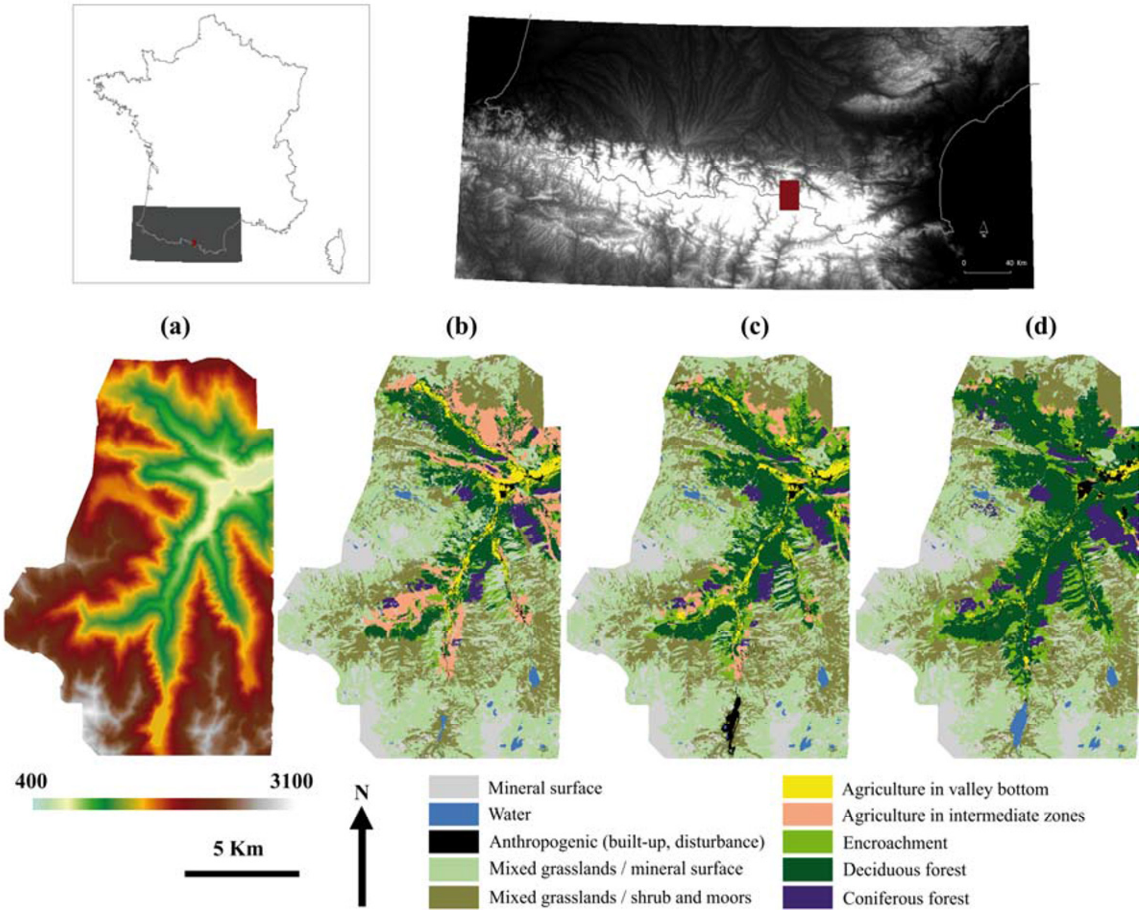

Figure 2 Map of the Vicdessos valley, with (a) altitude (in meters) and land use and land cover in (b) 1942, (c) 1983 and (d) 2008.

selected maps are shown in Figure 2) using a large set of images covering the entire study area. Historical black and white photographs produced by the French national mapping agency were used to cover the period from the 1940s to the 1980s and true color photographs from the 1990s to 2008.

Due to the high rate of land abandonment since the beginning of the 20th century (Galop et al 2011), the study site is currently subject to increasing landscape encroachment and reforestation. Agro-pastoral activities have declined considerably resulting to forest re-growth some decades later (Figure 3 – for further details on rates estimation, see Houet et al. 2012). The spontaneous reforestation of the three landscape units that make up the traditional agro-pastoral system (valley bottoms, intermediate areas, uplands, see Gibon 2009) has been characterized by different dynamics. Because the steep slopes of the intermediate areas made access difficult, these were the first to be abandoned at a large scale, and exhibited the highest reforestation rates (approx. 55 ha/year) from the 1950s until the late 1970s. Valley bottoms were also affected by reforestation, mainly in the 1970s-1980s. Today, the uplands are at stake: decreasing agro-pastoral activities have led to a major reduction in grazing pressure (land use extensification) which favored reforestation, with forest regrowth rates similar to the highest rates observed in the intermediate zone (53 ha/year between 1993 and 2008) (Houet et al 2012). This phenomenon is similar to that observed in other valleys in the eastern and central French Pyrenees (Sheeren et al. 2010) and in the eastern Spanish Pyrenees (Cohen et al. 2011).

1.3 Simulation model: description and parameterization

Prospective simulations were conducted using the Land Change Modeler (LCM) tool. LCM is an integrated LUCC modelling and environmental assessment module included in the IDRISI GIS and Image Processing software developed by Clark

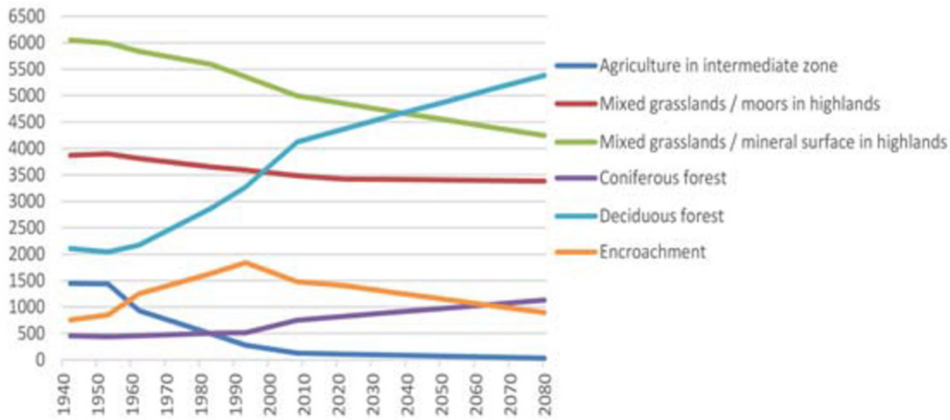

Figure 3 Past and future LUCC trends (in ha): the surface area of different types of land cover surfaces are derived from land cover maps compiled using historical aerial photographs (1942, 1953, 1962, 1983, 1993 and 2008) and future changes are estimated using the Markov chains available in the Land Change Modeler.

Labs (Eastman 2012). It is a pattern-oriented simulation tool that is particularly suitable for analyzing change and projecting spatial trends of LUCC (Houet et al. 2014). The most common simulation methods are included in the package and a user-friendly interface helps the user parameterize them as summarized by Mas et al. (2014).

Generally, two steps are required to simulate LUCC using LCM. The first step is model calibration. In our case, this step was based on two input land cover maps from different periods and a set of user-defined input driver variables that made it possible to create suitability maps (one for each land cover transition) of future change from past land transitions. Suitability maps of future LUCC can be estimated using either a multi-layer perceptron neural network (MLPNN), a logistic regression (LR), or a similarity-weighted instance-based machine learning tool (SimWeight). The driver variables can be static or dynamic. Dynamic variables such as the distance to a specific land cover are recalculated at each iteration over the period covered by the simulation. This option makes it possible to iteratively update the suitability map concerned at each stage of the simulation defined by the user. Once the model is calibrated, the second step is to simulate future changes while accounting for constraints and planning strategies. In LCM, the quantity and allocation of change is modeled by Markov chains with respect to the past transitions. Model calibration is acknowledged to be the first and most critical step in any LUCC modeling process (Santé et al. 2010). Learning consistent transition rules to accurately reproduce the observed historical land use and land cover dynamics may be a difficult, sometimes impossible, task. Kolb et al. (2013) showed that the calibration step may not be able to reproduce past changes if the weight of the respective driving factors changes while they remain the only explanatory factors for the period under study.

In the present study, only two past land cover maps were used to project change and analyze uncertainty. The maps we used date from 1983 and 2008, and have a resolution of 10 × 10 m. They are particularly suitable for capturing the latest LUCC in the uplands. We only focused on the intermediate areas and uplands as they exhibited the highest rate of change, and remaining agricultural fields in the valley bottom accounted for only 167 ha in 2008 (i.e. 1% of the study area). Only the main land transitions were modelled in LCM. Four transitions were defined based on the observed LUCC and endorsed by expert-knowledge, as types of land covers able to change into:

'Mixed Grasslands and mineral surface' to 'Mixed Grasslands and moors';

'Mineral surface, Mixed Grasslands and mineral surface, Mixed Grasslands and moors, Agricultural land of intermediate zones' to 'Encroachment';

'Agricultural land of intermediate zones, Encroachment' to 'Deciduous forest';

'Mixed Grasslands and moors, Encroachment' to 'Coniferous forest'.

Because LCM is an inductive pattern-based model (Overmars et al. 2007), some transitions may appear to be inaccurate if they are based on changes in vegetation. Indeed, the encroachment process is continuous and spreads step by step. In the model, the process is simplified and reproduced from observed LUCC between the input maps. Future LUCC are estimated using Markov chains. This method implies that future trends are linear (Coppedge et al. 2007) (Figure 3). Compared to past LUCC trends, the estimated amount of future deciduous and coniferous forests may appear to be slightly underestimated. This is because all the transitions are not taken into account. However, because this land demand can be manually defined/modified and thus improved using other approaches (e.g. participatory or model-based estimation), we decided to use these estimations for all the simulations to make their comparison possible.

Potential transitions in the future were defined from a set of driver variables using the MLPNN method, which made it possible to estimate the respective influence of each variable in the period 1983 to 2008. Three types of driving factors were distinguished (Table 1): (i) those that depend on land use and land cover such as the agro-pastoral areas and the likelihood of one land over type being transformed into another; (ii) environmental drivers, which depend on the geology and the relief (altitude, slope and aspect); and (iii) geographical drivers, which represent the positive or negative influence of the proximity of a land cover (distance to). Fifteen driving factors were used for each transition, these factors can be either quantitative (e.g. real values of Euclidian distance) or qualitative (e.g. geological or land cover classes) as existing methods to evaluate their respective weight can use one or both types of data (Mas et al 2014). The type of driving variables may affect modelling, as logistic regression requires quantitative data, the weight of evidence method requires qualitative inputs, and MLPNN can use both. We assumed that the spatial rendering of these driving factors influences the simulation of landscape patterns. Hence, quantitative values were also converted into qualitative variables using discretized empirically defined buffered distances (200 m in width) and classes of slope, altitude and aspect. Their significance was assessed using Cramer's V index and the MLPNN Accuracy Rate

Table 1 List of driving factors (geophysical and geographical) and their Cramer's V values that express their association (ranging from 0 to 1 – a value of 0.1 means the driver has predictive power, Eastman 2012) with observed changes

Transition to			Grasslands and Moors	Encroachment	Deciduous	Coniferous
Land covers/Land uses		Likelihood of a given land cover	0.19	0.23	0.29	0.08
		Land use zones	0.36	0.16	0.67	0.22
Geophysical	Quantitative/qualitative values	Geology	0.26	0.23	0.39	0.33
		Slopes	0.08 / 0.06	0.07 / 0.07	0.06 / 0.03	0.09 / 0.08
		Altitude	0.39 / 0.35	0.23 / 0.20	0.60 / 0.52	0.17 / 0.15
		Exposition	0.11 / 0.11	0.12 / 0.10	0.09 / 0.10	0.11 / 0.09
Geographical	Neighborhood influence expressed by Euclidian distance to ... (quantitative values) / Buffered distance to ... (qualitative values)	Mineral	0.20 / 0.20	0.12 / 0.12	0.26 / 0.25	0.10 / 0.10
		Anthropogenic	0.27 / 0.25	0.23 / 0.24	0.51 / 0.53	0.21 / 0.21
		Agriculture in valley bottom	0.33 / 0.29	0.27 / 0.28	0.64 / 0.65	0.28 / 0.25
		Agriculture in intermediate zones	0.26 / 0.26	0.30 / 0.29	0.50 / 0.50	0.17 / 0.17
		Mixed grasslands and mineral	0.28 / 0.28	0.11 / 0.10	0.41 / 0.35	0.18 / 0.16
		Mixed grasslands and moors	0.49 / 0.42	0.12 / 0.12	0.33 / 0.30	0.13 / 0.12
		Encroachment	0.32 / 0.33	0.33 / 0.32	0.59 / 0.57	0.21 / 0.18
		Deciduous	0.40 / 0.40	0.29 / 0.30	0.72 / 0.70	0.22 / 0.22
		Coniferous	0.24 / 0.23	0.27 / 0.27	0.55 / 0.55	0.56 / 0.55

(AR). Cramer's V index evaluates the statistical significance of the factor for the LUCC concerned. A value greater than 0.1 is considered to be significant and is integrated in the model, but a factor with a lower value can also be integrated if it helps explain a minor LUCC (Eastman 2009). The accuracy rate expresses the capacity of the neural network to find the best combination of driving factors based on back-propagation (i.e. with self-learning and self-modification capacities).

1.4 Model calibration based on driving variables

Firstly, whatever the qualitative and quantitative form of the other drivers, all driving factors except the slope driver had a significant influence on observed LUCC. Secondly, in most cases, the quantitative data had slightly higher V values than those obtained with qualitative data. Thirdly, although the most significant driving factor was the distance to the corresponding land cover for all transitions, the second most significant driving factor varied from one transition to another. For instance, altitude was the second most significant driving factors for the transition to deciduous forest while distance to agricultural land in the valley bottom was the second most significant driving factor for the transition to coniferous forest.

The accuracy rates obtained for each transition were all greater than 70% (Table 2) meaning that the spatial allocation of at least seven out of 10 pixels that underwent one of the transitions was explained by the selected driving factors. For the transition to coniferous forest, quantitative and qualitative data explained respectively 94.74% and 92.10% of the spatial allocation of changes observed in the period from 1983 to 2008. The unexplained part may be due to driving factors that were not taken into account, or to randomness. The spatial rendering did not appear to affect the performance of the MLPNN, i.e. the AR were similar for both types of data used, except for the transition to encroachment, which had a smaller AR using qualitative data (70.1%) than with quantitative data (85.32%). These AR may differ for two reasons: (1) the pixels, which are randomly chosen by the model to train the neural nets, are not the same, although the modeler can control their number; (2) the spatial rendering of driving factors is not the same either, which obviously influences the calculation of the weights of the neural net.

Table 2 **Accuracy rates obtained from the MLPNN for each transition using quantitative (left column) vs. qualitative (right column) driving factors**

	Quantitative	Qualitative
Transition to Grasslands and Moors	76.45%	78.60%
Transition to Encroachment	85.32%	70.10%
Transition to Deciduous forest	71.31%	74.88%
Transition to Coniferous forest	94.74%	92.10%

1.5 Model projections based on land use change scenarios

Two scenarios were run to project LUCC for the year 2080, to identify significant LUCC and for hydrological assessment purposes (Sczypta et al. 2015). The focus was only on land abandonment. Past urban growth dynamics to the detriment of agricultural land in the valley bottom were disregarded.

The first scenario called "Model-based Business As Usual" (MBAU) assumes that the model is able to simulate observed agropastoral land uses based on the given input land cover maps and driving factors. Its aim is to continue the observed grazing activities in the uplands over the calibration period. This scenario should not be confused with a trend scenario: based on the observed trends, pastoral pressure (i.e. livestock density) would assume a decrease in the future, whereas it would be considered as constant by the model. More precisely, agricultural statistics show that, in practice, the Ariège Department has not been affected by the major reduction in livestock that was predicted in the 1970s. Grazing pressure decreased slightly (-10%) in the mountainous area[1)] between 1979 and 2000 even if the number of farms was halved (Eychenne 2008). The main change was in the type of herd: the number of cows increased by 25% while the number of sheep decreased by the same amount. This is extremely

1) In France, 'mountainous areas' is the term defined as grouping municipalities located above 1200 m a.s.l.

important for LUCC modelling as, unlike sheep, cows cannot graze remote less accessible zones in the uplands. In that sense, because the grazing pressure on the Vicdessos valley has not yet undergone the qualitative change in the type of herds that occurred in the rest of the Department, and considering that it is still mainly grazed by herds of sheep (Eychenne 2006), we can assume that the calibration phase will underestimate possible LUCC and the amount of future natural reforestation. Hence, even if this scenario does not track the past agro-pastoral trends, it can estimate what the future would be like if it were possible to maintain current agro-pastoral activities throughout the model parameterization.

A second scenario, called "Prioritizing High Value Uplands[2)]" (PHVU), assumes a new strategy in agro-pastoral land use: as the grazing pressure decreases in the future and the type of herds changes, the best uplands, in terms of forages and accessibility, will concentrate all pastoral activities in order to maintain and increase the grazing pressure (up to 100%). The aim of this scenario is to stop reforestation, but to abandon less accessible and remote areas (Figure 4). According to the agropastoral administration of Ariège, the 'best uplands' are those whose grazing pressure is greater than 50%.

1.6 Experimental protocol with comparison of projected changes

The experimental protocol accounts for the same land demand and transitions in both scenarios, while also assessing the respective and combined influence of qualitative vs. quantitative and static vs. dynamic drivers. Hence, four simulations were run for each scenario, each considered to be as probable as another with respect to the significance of the driving factors selected and the AR obtained. These four simulations are four possible variations of the scenario. As mentioned previously, it is assumed that the quantitative and qualitative representations of the driving factors help improve the simulation of future LUCC. LCM can make both types of driving factors dynamic in order to integrate the feedback effects of future neighboring LUCC. For Euclidian distance (quantitative) driving factors, the distance to a land cover is recomputed at each stage of the simulation. For buffered distance (qualitative) drivers, at each stage, we recomputed the distance (reclassified discretized empirically defined buffered distances 200 m in width), to which the estimated probabilities from the calibration period are assigned. The combination of these options (dynamic vs. non dynamic drivers and quantitative vs. qualitative driving factors) led to the four above-mentioned simulations we named as follows: *QualNon* (Qualitative and Non-dynamic driving factors), *QualDyn* (Qualitative and Dynamic driving factors), *QuantNon* (Quantitative and Non-dynamic driving factors), *QuantDyn* (Quantitative and Dynamic driving factors).

The comparison of the simulated land cover maps made it possible to assess the influence of (i) dynamic vs. non-dynamic driving factors and (ii) the spatial rendering of these driving factors

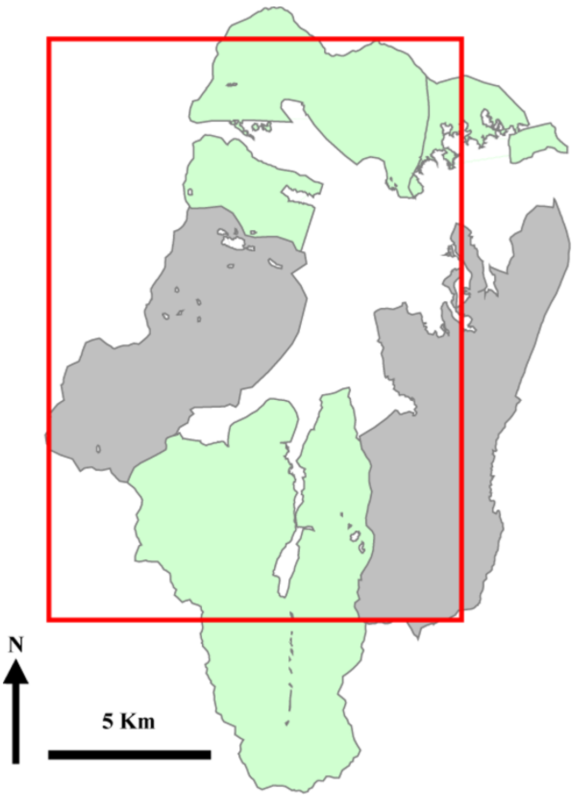

Figure 4 Location of the uplands in the Vicdessos valley (in color) and those that would be abandoned (in gray) in the PHVU scenario. The red rectangle delineates the map's footprint.

2) An upland is defined as the administrative units of summer grazing pasture that are eligible for UE support. The uplands in our study area cover all the summer grazing areas and are defined, delimited, and monitored by the agro-pastoral administration of the Department of Ariège.

(Quantitative vs. qualitative driving factors) on the spatial uncertainty of future landscape changes. Moreover, following Mas et al. (2012) and Jenerette and Wu (2001), landscape metrics were used to distinguish between the simulations and to compare them with those obtained from the historical land cover maps. Five metrics were selected to measure forest fragmentation over time: number of forest patches, mean size and standard deviation of forest patches, mean Euclidian Distance between forest patches and their clumpiness. These metrics made it possible to assess the influence of these parameterization options on the model's ability to simulate LUCC that are consistent with those observed in the past. We assume that the more the values are able to pursue or mimic past trends, the more consistently the model will be parametrized to simulate future landscape patterns of land abandonment in a mountainous area.

Spatial uncertainty was computed by overlaying the multiple allocation of the land abandonment effect on LUCC (encroachment, natural deciduous and coniferous reforestation) inherited from the multiple simulations/scenarios (Verburg et al. 2010). Future uncertainty is the probability of occurrence, i.e. the more frequent the land abandonment effects occur in the combined simulations, the more likely it is that the location concerned will be affected. For this purpose, simulated reforestation LUCC were overlaid and the forest land cover in 2008 was retrieved in order to only account for new changes. Encroachment was also considered in the same way, as it results from land abandonment. We assumed that a cell exhibiting reforestation in two simulations and encroachment in another simulation would have a higher probability of being abandoned than a cell exhibiting only reforestation in two simulations. We also assumed that a cell exhibiting reforestation in one simulation would have a higher probability than a cell concerned by encroachment in several simulations, as forest can be preceded by encroachment.

Spatial uncertainty maps for both MBAU and PHVU scenarios were computed using the four model parameterizations defined above. The qualitative maps were converted into – relative – quantitative values. A probability of 1 was assigned to cells that were converted into forest in the four simulations, and 0 was assigned for unchanging land cover. The score decreased by 1/14 as 14 classes of changes were possible (from encroachment in one simulation, encroachment in two simulations, etc. until forest in three simulations and encroachment in one simulation, forest in four simulations). Future spatial uncertainty was assessed by computing mean and difference maps from the spatial uncertainty maps. A mean value of relative probability highlights locations where, considering both scenarios, land abandonment is most likely to occur. A difference map shows which probabilities mostly depend on one scenario rather than another. These two maps were used to assess the influence of the PHVU land use strategy.

2 Results

2.1 Influence of model parameterization

According to the landscape metrics extracted from the simulated LUCC, all simulations produced landscape patterns consistent with the past LUCC trends (Figure 5). For example, the mean size of forested patches tended to increase along with their mean size and standard deviation (Figure 5a and 5b).

Accounting for dynamic drivers favored the simulation of more scattered forested patches than accounting for non-dynamic drivers. *QuantDyn* and *QualDyn* increased the number of patches compared to *QuantNon* and *QualNon* (Figure 5c) thereby affecting their mean size and standard deviation (Figure 5a and 5b). Moreover, accounting for dynamic drivers strongly influenced their location with respect to other patches of forest: non-dynamic drivers tended to reduce the mean Euclidian distance between patches, while dynamic drivers did not (Figure 5d). Figure 4c depicts the tendency for forested patches to merge, i.e. reforestation was simulated contiguously from existing patches, while dynamic drivers allowed the emergence of new patches of forest (for example, between 2008 and 2022, there were more patches Figure 5c).

When qualitative drivers were parameterized as dynamic, they influenced the ability of the model to simulate reforestation patterns, as the mean size of forested patches and their standard deviation

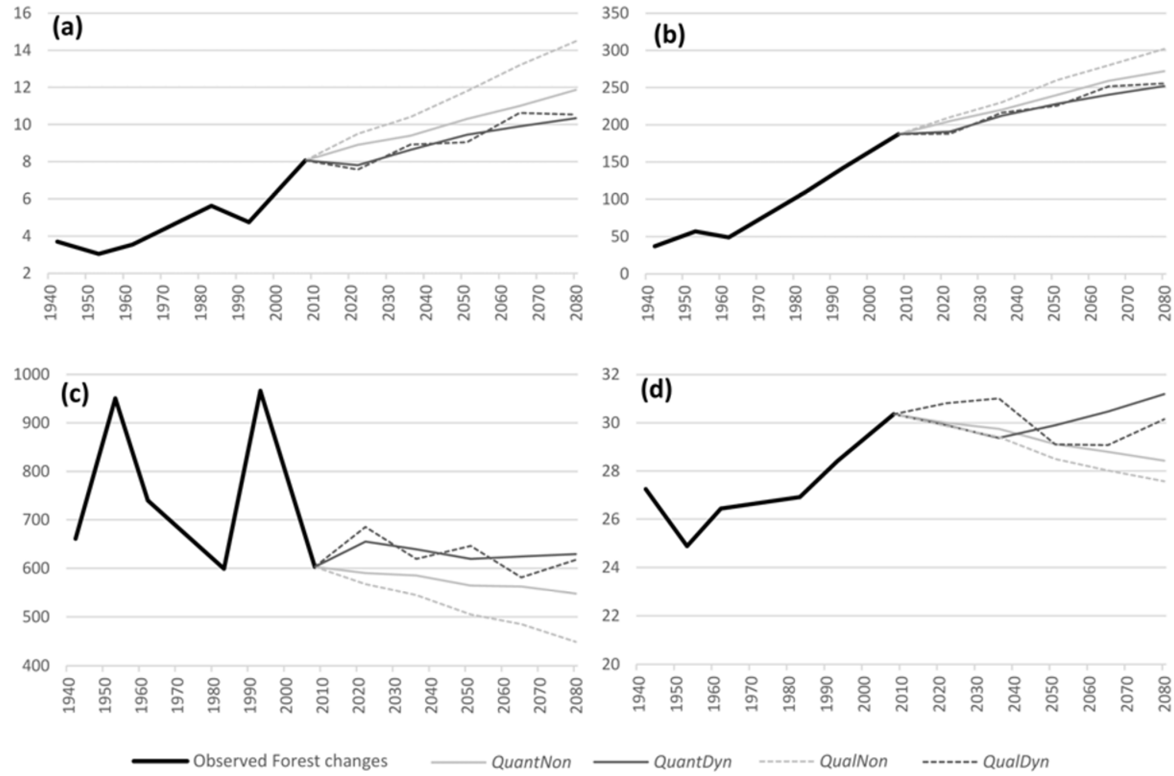

Figure 5 Changes in landscape metrics for the forest land cover (combining coniferous and deciduous forest) in the past (1942-2008) and the future (simulation up to 2080): (a) mean size (in ha) of patches and (b) their standard deviation (in ha); (c) the number of patches; (d) the mean Euclidian distance (in meters) between patches.

remained similar but their number changed. Qualitative drivers appeared to better reproduce the reforestation patterns observed between 1942 and 2008; the process takes place in three steps: (1) patches of forest emerge, thereby increasing their number, (2) contiguous growth of new and existing patches leading to (3) the merging of these patches, thus increasing their mean size and standard deviation. When used non-dynamically (light gray lines), these two types of drivers had different effects on reforestation patterns: qualitative drivers increased the contiguous effect of the reforestation due to the proximity of existing patches of forest.

The type of parameters (qualitative or quantitative, static or dynamic) had a major influence on the spatial uncertainty of future LUCC. The use of dynamic quantitative drivers affected spatial uncertainty in particular by reducing the extent of areas expected to change into the same type of land cover in both simulations (in gray and black – Figure 6) while enlarging areas affected by encroachment or reforestation in one of the two simulations (light and medium green / light and medium blue - Figure 6a). In this case, the areas colored light and medium green are those likely to change due to their proximity to simulated changes in land cover (in the northern, western and south-eastern parts of the valley). Conversely, areas colored light and medium blue are those likely to change due to the proximity of existing land cover in the original land cover map. Comparison of the simulated *QualNon* and *QualDyn* land cover maps revealed spatial uncertainty to be less sensitive to model parameterization. The areas expected to change into the same type of land cover (gray and black – Figure 6b) cover a total of 2075 ha and those expected to be converted into encroachment or forest in one of the two simulations add up to only 312 ha. Figure 6b shows that when the drivers are used non-dynamically (blue areas), the southern part of the valley is more likely to change while new patches of forest inherited from dynamic drivers are more dispersed over the whole study site.

The influence of qualitative/quantitative drivers is illustrated in Figure 7. When the drivers are used non-dynamically, the comparison of *QuantNon* and *QualNon* showed that simulated encroachment and forest allocated to the same

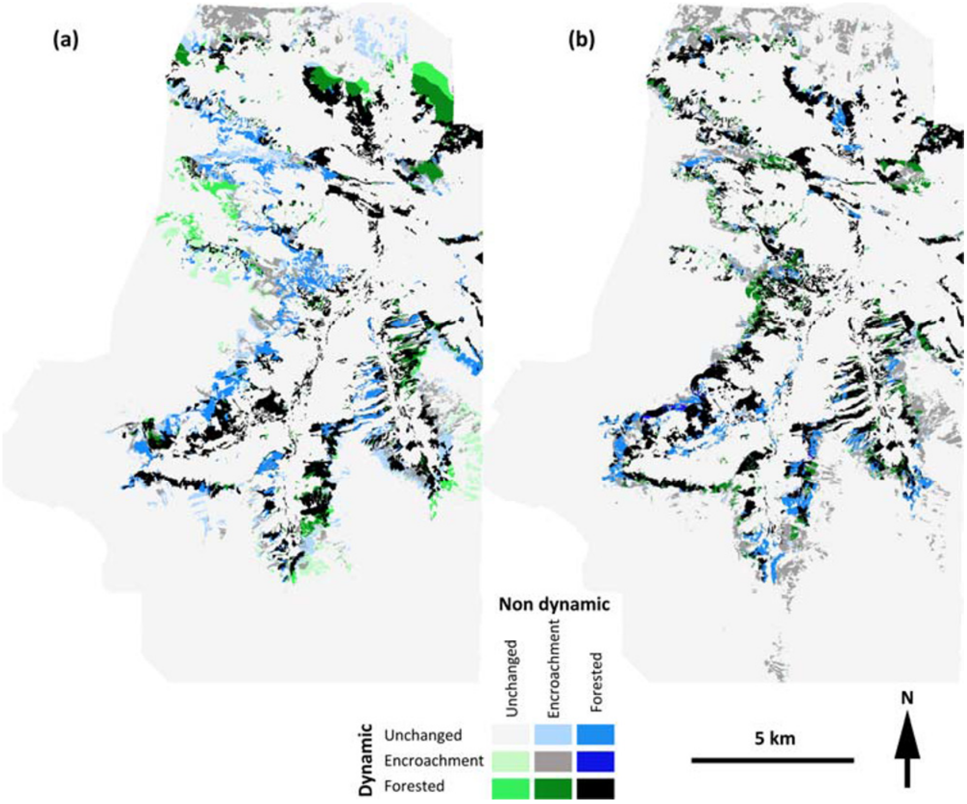

Figure 6 Comparison of the spatial uncertainty for (a) quantitative and (b) qualitative drivers used non-dynamically and dynamically.

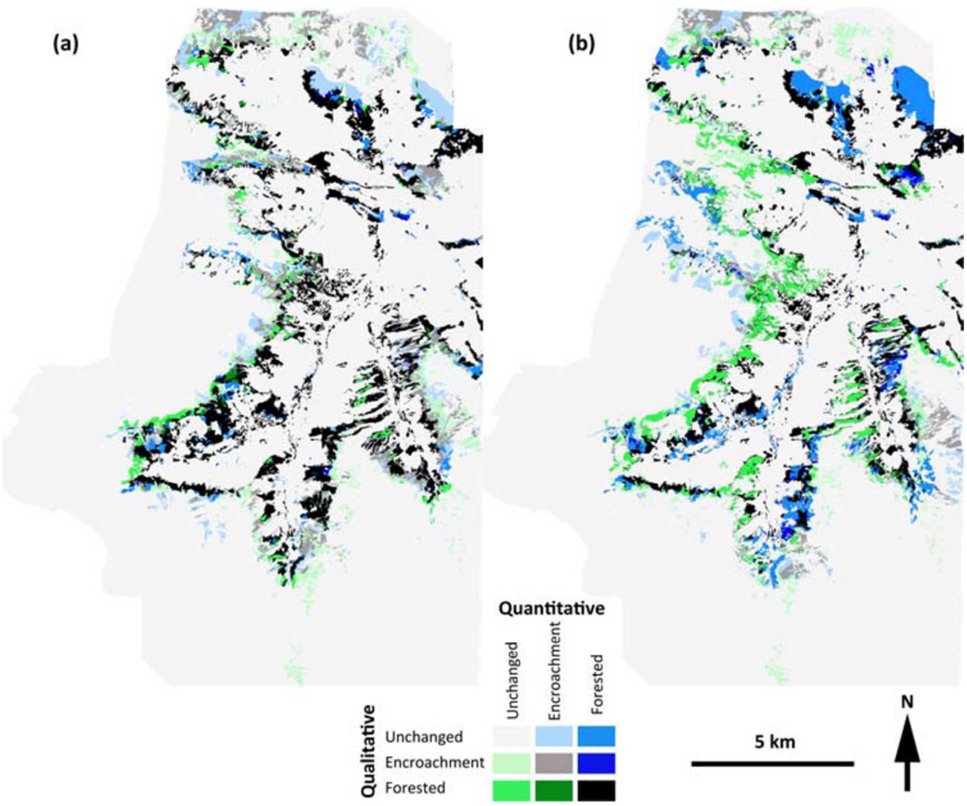

Figure 7 Comparison of the spatial uncertainty for (a) non-dynamic and (b) dynamic drivers using quantitative and qualitative spatial rendering.

Table 3 Estimation of the areas (in ha) concerned by encroachment and/or forest changes in at least one of the two simulations concerned (i.e. model parameterization)

Comparison of simulations	*QuantNon / QuantDyn*	*QualNon / QualDyn*	*QuantNon / QualNon*	*QuantDyn / QualDyn*
Encroachment (in only 1 simulation)	629.12	111.66	935.68	742.14
Encroachment (in both simulations)	474.82	780.9	683.71	289.48
Forest (in only 1 simulation)	649.95	346.89	353.53	1219.01
Encroachment or Forest (in both simulations)	296.74	312.5	52.8	184.46
Forest (in both simulations)	1166.47	1294.15	1436.74	922.02

location in the two simulations (in gray and black) predominates, adding up to a total of 2120 ha (Table 3). The main difference concerns the location of the simulated encroachment (light blue and green – Figure 7a), which accounts for 935 ha. Conversely, when drivers are used dynamically, their spatial rendering strongly affects the spatial uncertainty of simulated LUCC. More extensive zones are potentially concerned by land abandonment in one of the two simulations. When the drivers are dynamic, the result is a major increase in the areas suitable for natural reforestation (1219 ha) and encroachment (742 ha). Nevertheless, the correlated effect reduced the total area concerned by land abandonment in these two simulations (Table 3). Last but not the least, according to the results in Figure 5, the spatial rendering of drivers affects the simulated pattern of encroachment and natural reforestation: it can be seen that when they are used dynamically, qualitative drivers simulate new patches (scattered, sharpened and unsmoothed, sized, distance from each other, etc. in green in Figure 7b) with more likeness to past changes than quantitative drivers (in blue in Figure 7b). Conversely, this is not visible when the drivers are not dynamic (Figure 7a).

2.2 Influence of land use scenarios on land abandonment trajectories

The combination of all the simulations allowed us to assess the spatial uncertainty of future LUCC due to model parameterization in both MBAU and PHVU scenarios (Figure 8a and 8b respectively). These maps depict the zones that are potentially concerned by land abandonment (in color). These areas are equiprobable as both scenarios could happen. The respective probability of the two scenarios occurring in the future is not assessed here. While the four simulations were designed for a single scenario, each map of spatial uncertainty highlights where encroachment and natural reforestation are more likely to occur (from pink to purple) based on which parameters are chosen as inputs for the model.

The PHVU scenario led to a lower total area potentially concerned by land abandonment (3023 ha) than the MBAU scenario (3764 ha) while respecting the same demand for land (Table 4). The amount of land potentially concerned by encroachment alone is lower in the PHVU scenario (470 ha) than in the MBAU scenario (1254 ha). Areas exhibiting natural reforestation in at least one simulation, or encroachment at the same location in any other simulation, were similar as those exhibiting natural reforestation in at least two simulations with or without encroachment (736 ha and 717 ha respectively). The PHVU land use strategy showed its effectiveness: the uplands where grazing pressure has increased are particularly susceptible to encroachment. Conversely, some areas shown to be less likely to change in the MBAU scenario (in blue and green in Figure 8a) are shown to be more likely to change in the PHVU scenario (green and orange in Figure 8b).

Areas colored gray in the difference map (Figure 9a) do not depend on the pastoral land use strategy with different probabilities of encroachment (low scores) and/or natural reforestation (high scores) in the mean relative probability map (Figure 9b). Given their past trajectories and the absence of land use planning constraints, these areas are the most likely to change. Inversely, areas with a high probability of change and a high/low difference value are those that depend to a great extent on land use management. In summary, the mean probability map illustrates the possible degree of landscape reforestation due to land abandonment, while the difference map shows the degree of confidence users (modelers, stakeholders, decision makers) have in the effect of land abandonment.

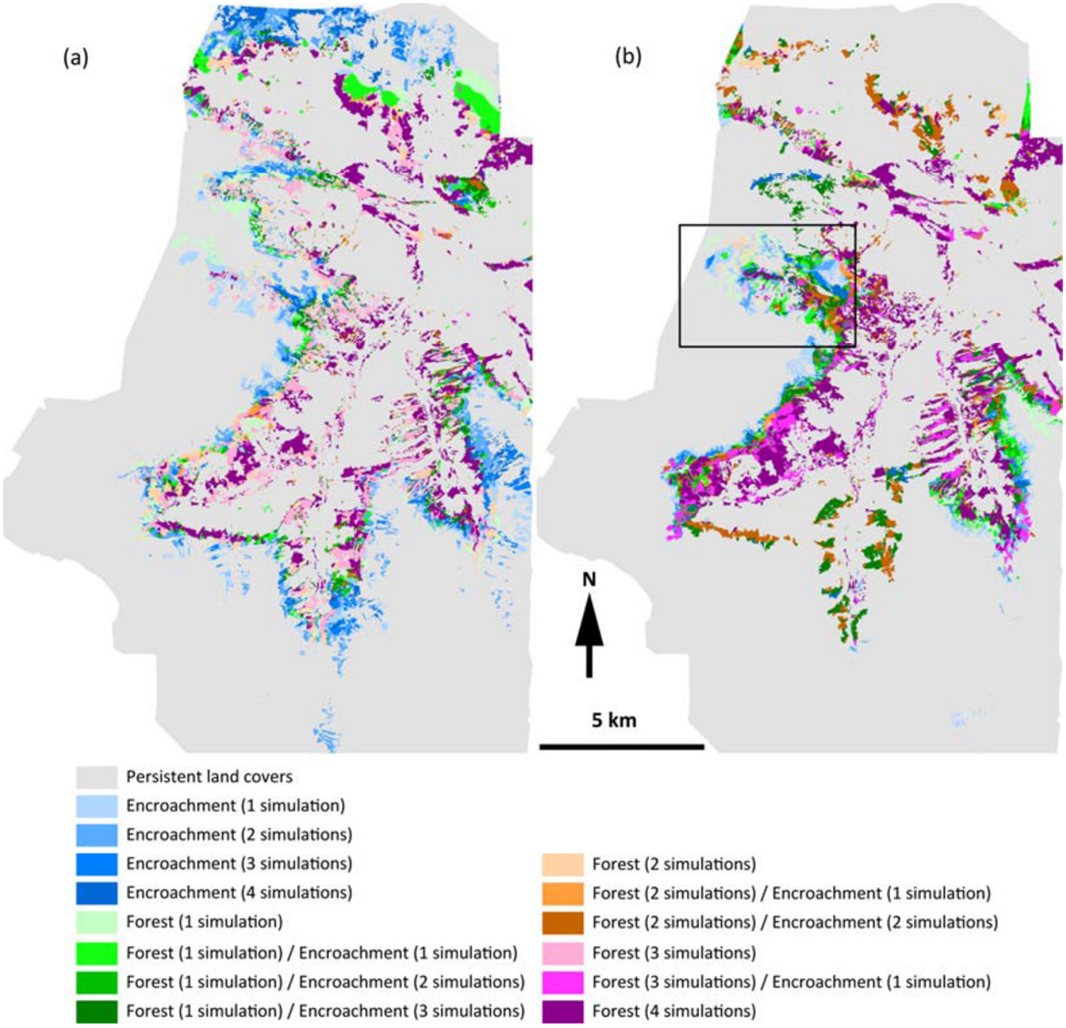

Figure 8 Spatial uncertainty of the (a) MBAU scenario and the (b) PHVU scenario combining all simulations (*QuantNon*, *QuantDyn*, *QualNon* and *QualDyn*).

Table 4 Estimation of the area (in ha) concerned by encroachment and/or forest changes in at least one simulation with the MBAU and the PHVU scenarios

Scenarios	MBAU	PHVU	Scenarios	MBAU	PHVU
Unchanged land cover	13886.39	14627.26	Forest (1 simulation) / Encroachment (1 simulation)	222.09	149.95
Encroachment (1 simulation)	373.57	226.27	Forest (1 simulation) / Encroachment (2 simulations)	86.89	111.18
Encroachment (2 simulations)	439.71	117.37	Forest (1 simulation) / Encroachment (3 simulations)	156.24	360.95
Encroachment (3 simulations)	216.57	52.61	Forest (2 simulations)	284.37	79.15
Encroachment (4 simulations)	224.62	73.99	Forest (2 simulations) / Encroachment (1 simulation)	31.53	56.7
Forest (1 simulation)	251.56	113.88	Forest (2 simulations) / Encroachment (2 simulations)	72.55	423.6

To give an example, a hot spot – called the Bassiès valley (west central part of the Vicdessos valley indicated by the black rectangle in Figure 8b) – is more clearly revealed. Indeed, some of the patches that are highly likely to change into forest are located in this valley (Figure 9a) but are not more influenced by one scenario than by another (light blue and gray values in Figure 9b). This means that if this area is not grazed as much as was the case during the period 1983-2008, it will be

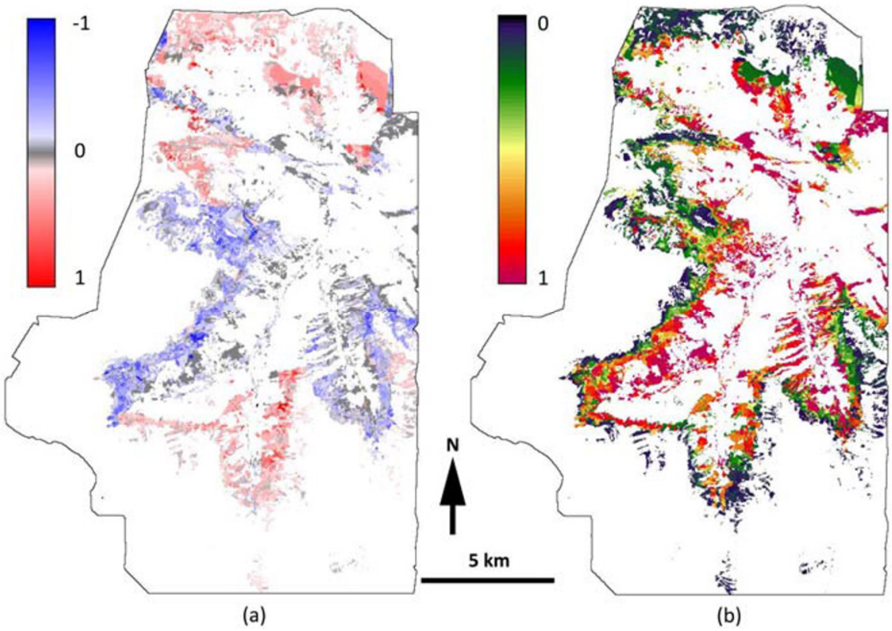

Figure 9 Comparison of the spatial uncertainty maps of the two scenarios: (a) mean values of probability of land abandonment relative to all simulations – a value of 1 highlights natural reforestation in all simulations; (b) the difference map between the MBAU and the PHVU scenarios – a value of -1 highlights natural reforestation in the four simulations of the PHVU scenario and inversely.

particularly affected by natural reforestation.

3 Discussion

3.1 Mapping spatial uncertainty: a tool for prioritizing land management actions

Mapping the spatial uncertainty of future LUCC will help land managers as it makes it possible to identify areas where socio-ecological services are at stake or where risk assessment is possible by overlaying maps of spatial uncertainty with maps of natural hazards (rock fall, avalanche corridors, etc.). Areas where the probability of LUCC occurrence is the highest are the most vulnerable. If social, economic, or ecological stakes exist, land managers for these areas should take priority actions. If other zones are less vulnerable, they could be more important for human or environmental purposes. In any case, spatial uncertainty maps make it possible to rank the stakes in order of priority. Here, we mainly focus on pastoral activities because the areas concerned by encroachment and/or natural reforestation would otherwise be permanently lost. The investments required to recover usable land would be high and the use of fire would seriously affect natural processes, and, in addition, would require appropriate pastoral practices. In any case, mapping future LUCC and their uncertainties can be particularly helpful to reconciling biodiversity conservation and human livelihoods (Mitchley et al. 2006).

This type of uncertainty map can be distinguished from the suitability maps usually produced as model outcomes (Camacho Olmedo et al. 2013). Suitability maps provide useful information about suitable areas concerned by land abandonment for a single scenario. Future uncertainty maps provide similar information for multiple scenarios, and consequently reduce the uncertainty due to the future. This study compares only two scenarios, but further work based on this approach (for e.g. Vacquié et al. 2015), and combining more scenarios would lead to a more complex but nevertheless concise outcome. The present study made it possible to distinguish the inherent uncertainty of a scenario resulting from model sensitivity to parameters, and the ensemble uncertainty resulting from the different scenarios (Figure 10). Further studies should be conducted in the same way to better assess the quantitative – inherent – uncertainty (due to random LUCC allocation) for a single scenario and the quantitative – ensemble – uncertainty for multiple

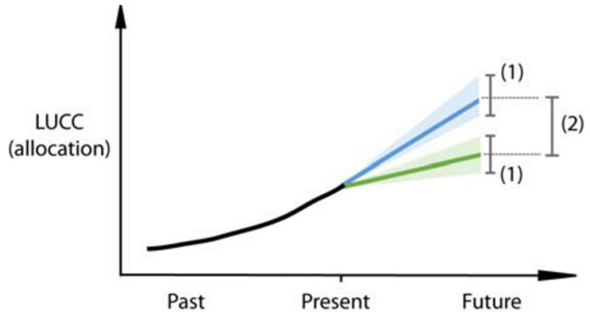

Figure 10 Different types of uncertainties are distinguished: (1) the inherent uncertainty of a single scenario inheriting from the model parameterization (often assimilated to variations due to random LUCC allocations for e.g.) and (2) the ensemble uncertainty defined by multi-projections (multi-scenario – in green and blue here - and/or multi-model) which combination allows to delineating the uncertainty due to the future.

scenarios. A first step could consist in multi-model ensemble simulations, as LUCC allocation varies from one model to another. A second step could combine multi-model and multi-scenario ensemble estimations. A third step would account for the different probabilities of occurrence for each scenario based on multi-criteria analysis and/or participatory approaches. Combining the different types of uncertainty in a single map is essential to reduce the dimension of uncertainty concerning future land changes.

3.2 LCM model and parameterization: advantages and drawbacks

From the point of view of a simulated land abandonment pattern, our first conclusion concerns the use of either dynamic qualitative or non-dynamic quantitative drivers. The appropriate choice needs to be made considering the spatial resolution of the input data, which, in addition to the model used, may also have an influence. Indeed, the proposed approach may not be appropriate for use at a coarser scale, where landscape patches are composed of very few cells. Other models contain specific parameters to simulate landscape patterns (e.g. Dinamica-Ego with the patcher and expander parameters – Soares-Filho et al. 2002), so it would be useful to assess the influence of the spatial rendering of qualitative drivers on model outcomes. Our results only concern the land cover in 2080 and intermediate maps need to be verified. The landscape metrics used to characterize the simulated dynamics of land abandonment corroborate this conclusion as non-dynamic qualitative and dynamic quantitative drivers produced the two most extreme patterns (Figure 4). Nevertheless, dynamic drivers are supposed to better account for the combined effect of (i) newly simulated encroachment patches that will be able to make the transition to forest at the next iteration and (ii) the proximity of encroachment and forest to these new patches.

The land change modeler has its own advantages and drawbacks that may influence the results. Enabling and/or disabling some transitions between land covers affects the model's capacity to allocate the estimated land demand. Because the same transitions were used for all our simulations, this influence was not apparent. However, some tests made to mimic the process of land cover change, i.e. respecting an intermediate land cover state (for example, disabling the direct transition from agricultural land in intermediate zones to deciduous forest, in favor of the two following transitions: agricultural land in intermediate zones to encroachment, and subsequently encroachment to deciduous forest) led to a marked decrease in allocated LUCC. We assume this underestimation of future LUCC was due to the selection of land cover transitions that limit the allocation of the overall amount of expected changes. Moreover, the land demand estimation strongly depends on the land cover maps used as inputs. The choice of historical input maps is critical and there are no rules to optimize it. Here we assumed that the most recent 25 year period during which the main LUCC were captured are representative of current dynamics. A longer period would have led to underestimation of the demand for land, as more changes occurred recently than earlier. Moreover, in the uplands, LUCC began to occur in the late 1980s. We recommend defining the input maps according to the LUCC of interest. However, pattern-based models using input maps for their calibration are automatically constrained by these data. For example, many studies predict a regime shift in alpine vegetation and/or forests in mountainous areas (Peñuelas and Boada 2003; Beckage et al. 2007; Lenoir et al. 2008; Brandt et al. 2014). Converted into pattern-based models parameterization, a regime shift would consist in modifying the respective probabilities of the altitudinal ranges considered. But the weight of the altitude ranges estimated by LCM during calibration remains fixed throughout the simulation (Kolb et al. 2013), meaning this assumption is not suitable for this kind of model. Accounting for feedback effects due to the proximity of future LUCC through dynamic processes is the best way to compensate for this drawback.

From a model user's point of view, the LCM is particularly user-friendly and flexible, and has already been compared with other available and comparable LUCC models (Mas et al. 2014). Its main functionalities are clearly described and the available tutorials are very helpful. However, it needs to be used in an expert mode to account for qualitative dynamic drivers. For example, the model is capable of making any driver dynamic through the development of macros. As there is no tutorial to explain how to incorporate them in the model, we have included one in appendix 1. Another minor limitation is that although the constraint map defining the pastoral land use strategy can be set for specific transitions, it cannot be activated for a specific date or modified during the course of the simulation, which would be more convenient for assessing breaking trend scenarios.

4 Conclusions

The proposed method for assessing the future uncertainty of LUCC, which focuses on the influence of land abandonment on natural afforestation in a mountainous region, was adapted from the multi-model ensemble approach (Peng et al. 2002): we used an uncertainty analysis approach (Crosetto et al. 2000) to identify and evaluate the confidence intervals resulting from model parameterization for one scenario and applied it to two land use scenarios. Model parameterization was based on the use of identical drivers represented by a quantitative or a qualitative (discretized) mode and in a static or dynamic mode. Our first results show that dynamic and qualitative spatial rendering tend to improve the simulation of landscape patterns and dynamics, although further studies are now required to validate this result. The combination of simulations made with these four possible modes of parameterization provided a map of uncertainty of land abandonment in terms of encroachment and reforestation. This map illustrates the inherent uncertainty caused by model parameterization. The combination of these maps in two land use scenarios produced a future uncertainty map of land abandonment illustrating the ensemble uncertainty due to the exploration of the future. This resulting map can be particularly helpful to rank the land management strategies accordingly to stakes considered. For instance, future reforestation may have controversial effects on pasture activities although it may reduce landslides, soil erosion or avalanche risks. The identification of the areas potentially concerned by encroachment and/or reforestation may help reconciling biodiversity conservation and human livelihoods. Finally, we discussed (1) the usefulness of maps that could help land managers prioritize management actions while accounting for other scenarios and (2) the advantages and drawbacks of the model to help modelers in their choice of a model, which is a precondition for future studies.

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