



HAL
open science

Simulating interactions between land-use and land-cover changes for prospective scenarios with FORESCEM

Gaëtan Palka, Thomas Houet

► **To cite this version:**

Gaëtan Palka, Thomas Houet. Simulating interactions between land-use and land-cover changes for prospective scenarios with FORESCEM. 2025. <hal-05121081>

HAL Id: hal-05121081

<https://hal.science/hal-05121081v1>

Preprint submitted on 19 Jun 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY 4.0 - Attribution - International License

1 Simulating interactions between land-use 2 and land-cover changes for prospective 3 scenarios with FORESCEM.

4 Gaëtan Palka ^{1,2,3,*}, Thomas Houet ^{1,3}

5 1. LETG-Rennes COSTEL UMR 6554 CNRS / Université Rennes 2, Place du Recteur Henri Le Moal,
6 35043 Rennes Cedex, France

7 2. UR 1210 CEDETE, Université d'Orléans, 10 rue de Tours, 45065 Orléans, France

8 3. LTSER "Zone Atelier Armorique", CNRS, Rennes, F-35043, France

9 * Corresponding author: gaetan.palka@univ-orleans.fr

11 Abstract

12 Anticipating socio-environmental impacts of spatial planning strategies is a prerequisite for
13 sustainable development design. Land change models are increasingly employed to evaluate the
14 impacts of spatial planning on land use and land cover (LULC), and their subsequent effects on
15 ecosystem services and environmental resources. This paper presents a process-based model—
16 the FORecasting landscapE SCEnarios Model (FORESCEM)—designed to spatially simulate
17 future LULC changes based on narrative scenarios developed through participatory or expert-
18 driven approaches. The model enables the assessment of the effects of interactions among LULC
19 changes within human-managed landscapes. Validation results demonstrate the model's
20 capability to replicate both natural and anthropogenic dynamics, effectively simulating trend-
21 based and trend-breaking LULC trajectories under contrasting scenarios.

22 1 Introduction

23 Both land use and land cover changes (LUCC) critically affect land-atmosphere exchanges and
24 exert significant influences on climate regulation, water and soil quality, biogeochemical cycles,
25 biodiversity, and ecosystem services (UNEP, 2002; Lambin & Geist, 2008; Akber et al., 2018).
26 Evaluating potential future LUCC and their associated impacts has been recognized as a key
27 priority in land change science, given their central role in global environmental change (Lambin &

28 Geist, 2008). At the same time, effectively integrating considerations of climate, water and soil
29 quality, biogeochemical processes, biodiversity, and ecosystem services into spatial planning
30 remains a complex and persistent challenge (Wilson & Piper, 2008; Edman et al., 2011; Albert et
31 al., 2020; Wang, 2001).

32 Exploring medium- to long-term future land-use and land-cover changes (LUCC) has become
33 essential for the development of resilient and adaptive strategies. The integration of dynamic,
34 spatially explicit models with scenario-based approaches has emerged as a widely adopted and
35 effective method for projecting future LUCC (Dorning et al., 2015; Xiang & Clarke, 2003; Couclelis,
36 2005). These approaches are frequently employed to evaluate the implications of current or short-
37 term land management plans and policies, particularly in identifying high-risk areas for natural
38 hazard mitigation and in supporting decision-making processes for stakeholders. A persistent
39 challenge in LUCC modelling lies in adequately capturing the interactions between land use and
40 land cover changes (Verburg et al., 2016). While the concepts of land use and land cover are
41 interrelated, they differ in fundamental ways that are critical when analyzing, modeling, and
42 simulating socio-ecological systems. Two key differences are that "*[land cover] refers to the*
43 *composition of the features of the Earth's surface, while [land use] refers to the type of human*
44 *activity taking place at or near the Earth's surface"* (Cihlar & Jansen, 2001, p. 278) and the
45 relationship between land-use and land-cover is not a one-to-one relationship. Modeling one
46 (e.g., land cover) inevitably leads to a loss of information about the other (e.g., land use). However,
47 if interactions between land use and land cover changes are prime features of land change model
48 (Verburg et al. 2004; Verburg 2006; Güneralp et al. 2012), most of research in the literature
49 consider land uses and land covers as a whole, within one single land classification map, avoiding
50 the possibility to account for their interactions.

51 Simulating both land use and land cover changes, along with their interactions, requires the
52 integration of scenario-based frameworks with modeling tools—a methodology aligned with the
53 Story-And-Simulation (SAS) approach (Alcamo, 2008). In this context, scenarios are developed
54 through participatory processes or expert knowledge and are formalized as narratives that specify
55 where and how land-use changes may occur in the future, driven by anticipated policies or land
56 management strategies (Houet et al., 2017). These narratives, once formalized and translated into
57 quantitative variables, serve as inputs to parameterize land change models. The resulting
58 outputs—LUCC maps—not only visualize the narratives but also quantify the diversity of potential
59 future landscapes, enabling the construction of imaginative yet data-informed scenarios (Houet
60 et al., 2016). This approach aligns with the foresight paradigm (Godet, 1986), which emphasizes
61 the exploration of multiple plausible futures rather than a single deterministic projection.

62 In addition to simulating both land use and land cover changes and their interactions, the spatial
63 resolution of the model is a critical consideration. Fine-scale modeling of LUCC is essential for
64 accurately assessing the impacts of these changes on natural processes such as vegetation
65 dynamics (Bartha et al., 2004; Delheimer et al., 2023), as well as for informing the development
66 of context-specific and effective policy interventions (Mertens & Lambin, 1999). Nevertheless,
67 simulating LUCC at fine spatial resolutions remains a considerable challenge due to data
68 availability, computational demands, and the complexity of processes operating at multiple
69 scales (Houet & Verburg, 2022).

70 Furthermore, when coupled with scenario-based approaches, the use of LUCC models raises
71 critical questions regarding their validation (see the review by van Vliet et al., 2016). Commonly
72 employed validation techniques—such as assessments of location accuracy and spatial pattern
73 conformity—are particularly challenging to apply in land systems that are heavily influenced by
74 human activity. These methods generally assume that land systems evolve along current trends,
75 particularly in terms of spatial patterns, surface extents, and underlying drivers. While such
76 techniques are effective when applied to retrospective simulations—where modelled outputs
77 can be compared against observed historical LUCC data—they are inherently limited in the
78 context of mid- to long-term future projections due to the deep uncertainty associated with future
79 developments. In such cases, evaluating the accuracy of modelled outcomes becomes virtually
80 impossible, as there is no empirical reference against which to compare them.

81 Moreover, no LUCC model can perfectly reproduce reality (Mas et al., 2014). As suggested by
82 Houet et al. (2016), model validation should instead aim to enhance the plausibility of simulations
83 by assessing whether the modelled landscapes exhibit spatial patterns and dynamics that are
84 coherent, credible, and consistent with the underlying scenarios. This form of validation primarily
85 seeks to build stakeholder confidence in the modelling process. Although stochastic processes
86 may yield multiple plausible outcomes from the same parameter set (i.e., scenario), such
87 variability can actually foster stakeholder engagement by emphasizing the exploratory, rather than
88 predictive, nature of scenario-based modeling (Rigo & Houet, 2023; Rigo et al., 2022).

89 In this paper, we introduce a fine-resolution LUCC model specifically designed to simulate future,
90 spatially explicit, and contrasting scenarios. The model emphasizes a transparent and traceable
91 translation of stakeholder-informed narratives into model inputs, enabling the simulation of
92 interactions between land use and land cover changes. In this framework, land cover changes
93 refer to natural vegetation dynamics (e.g., transitions from meadows to forested states) as well as
94 changes in agricultural or forestry cover (e.g., crop rotations, transitions from planted to mature

95 forests). Land use changes, by contrast, are defined as land changes resulting from human
96 decisions— eg. deforestation, urbanization or abandonment. The model is applied to two case
97 studies: the Couesnon catchment in France, which employs participatory-based scenarios, and
98 the Pas, Miera, and Asón catchments in Spain, where scenarios are based on expert knowledge.
99 For model evaluation, we propose a two-pronged assessment approach: (1) a series of unitary
100 tests to verify rule compliance, and (2) a retrospective simulation of a past period to assess the
101 model's capacity to reproduce observed LUCC dynamics. The paper is structured as follows: first,
102 the model's architecture and underlying principles are described; second, the case study areas
103 and scenario characteristics are introduced; third, simulation results are presented; and finally,
104 the discussion addresses key features of the model and the implications of the validation
105 framework.

106 2 Materials and methods

107 2.1 Model design

108 2.1.1 Principles

109 The FORecasting landscapE SCEnarios Model (FORESEM) has been developed as a tool for
110 simulating land change processes at a fine spatial resolution, based on scenario narratives co-
111 constructed with stakeholders. To achieve this objective, the model integrates several key
112 features that underpin its conceptual and methodological framework (Figure 1):

113 (1) **Stakeholder narratives can provide information on both land uses (e.g., urbanization,**
114 **agriculture) and land covers (e.g., wheat fields, permanent meadows, natural**
115 **recolonization), as well as on the changes and interactions between them.** Accordingly, the
116 model explicitly distinguishes land use and land cover as separate data. It incorporates a set of
117 transition rules that govern changes within land uses, within land covers, and between land uses
118 and land covers, allowing for the simulation of complex and interdependent LUCC processes.

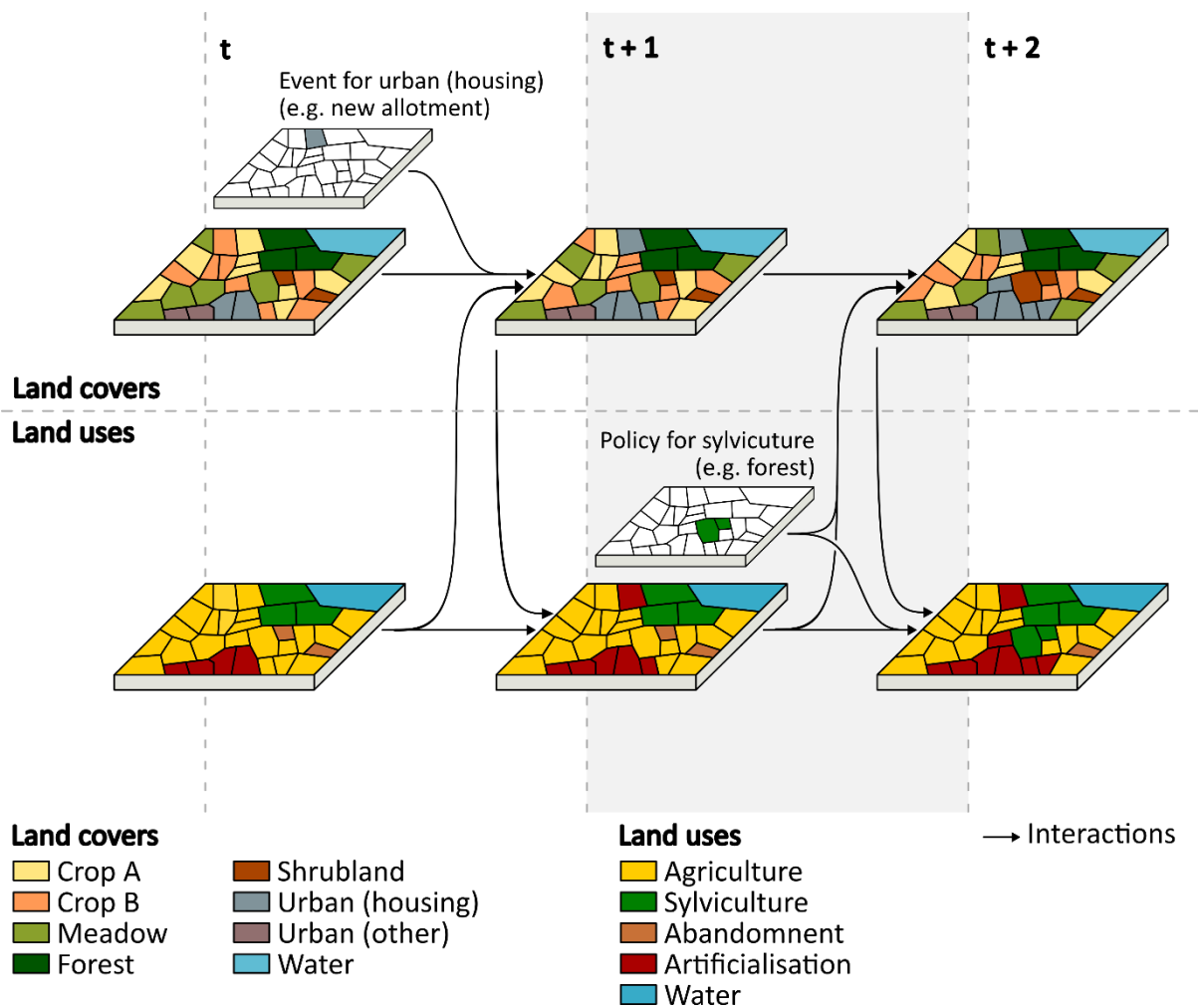
119 (2) **Stakeholder narratives may incorporate temporal variations in land-use and land-cover**
120 **changes, including shifts in rates, directions, or durations.** These changes may diverge from
121 historical trends (e.g., a reduction in the expansion of urbanized areas), involve abrupt disruptions
122 (such as the creation of a new housing estate resulting from planning decisions, or a randomly
123 located land-use shift due to deforestation or reforestation), or stem from unexpected events
124 (e.g., wildfires). To account for such dynamics, the model is implemented in Python to ensure

125 flexibility, adaptability, and ease of evolution. It includes mechanisms that allow for the punctual
126 and localized enforcement of specific land-use or land-cover changes. In FORESCEM, deviations
127 from LUCC trends are operationalized through two distinct mechanisms: *events* and *policies*.
128 Events represent sudden, discrete changes. They forcibly assign a specific land cover or land use
129 to a targeted location and, where necessary, update the corresponding land cover or land use. For
130 instance, a silvicultural project—modelled as an event in FORESCEM—applied to agricultural
131 land will force the land cover to shift to one compatible with silvicultural use. However, if the same
132 project is implemented in an abandoned area where land cover types (e.g., encroachment) are
133 already compatible with silviculture, a change in land cover is not required, and only the land use
134 is updated. Policies, by contrast, represent broader spatial constraints that either facilitate or
135 restrict the allocation of specific land uses or covers over the long term. These may function as
136 soft constraints—for example, guiding the gradual relocation of certain crops, thereby shaping
137 landscape evolution—or as hard constraints, such as zoning regulations that prohibit
138 urbanization outside designated areas. Unlike events, policies do not enforce immediate change
139 but influence land-use dynamics in response to evolving land demand.

140 **(3) Stakeholders seek to understand the mechanisms within the model that drive land-use**
141 **and land-cover changes.** This necessitates the use of explainable simulation models—such as
142 logistic regression or cellular automata—based on algorithms widely adopted in well-established
143 land change models (Van Vliet et al., 2016; Silva & Wu, 2012). FORESCEM builds upon this
144 foundation by employing transparent, interpretable modelling techniques and relying on
145 commonly available and easily understandable data sources, such as raster-based land cover
146 maps and spatially explicit, weighted explanatory variables.

147 **(4) Stakeholder narratives typically refer to changes occurring at the scale of coherent**
148 **elementary spatial units, often linked to perceived landscape structures.** In response,
149 FORESCEM operates at a fine spatial resolution, using *parcels* as the fundamental units of
150 simulation—reflecting the scale at which land development decisions are commonly made.
151 Parcels can be derived from existing spatial datasets (e.g., cadastral maps, or the LPIS database
152 for European agricultural land), or generated through landscape segmentation based on
153 environmental criteria such as slope, elevation, aspect, or geology. In FORESCEM, a parcel is
154 defined as a spatial object composed of a set of contiguous pixels (e.g., 10 m × 10 m) that undergo
155 change collectively. This object-based approach allows the model to generate spatially coherent
156 and realistic landscape patterns, enhancing its relevance for ecological assessments and land
157 planning applications (Houet et al., 2022).

158 *Figure 1: Conceptual description of the framework design accounting for interactions between*
 159 *land-use and land-cover changes: (1) if encroachment [as a land cover] appears or grows*
 160 *accordingly to the initialization, it converts the [land use of the] parcel as abandonment;*
 161 *urbanization or sylvicultural lands appears or grows accordingly to the initialization,*
 162 *it modifies the land-cover changes of parcels located within the concerned area;*
 163 *if new scenario-based land-use changes appear, it modifies the land-cover change processes.*



164

165 2.1.2 Architecture and functioning

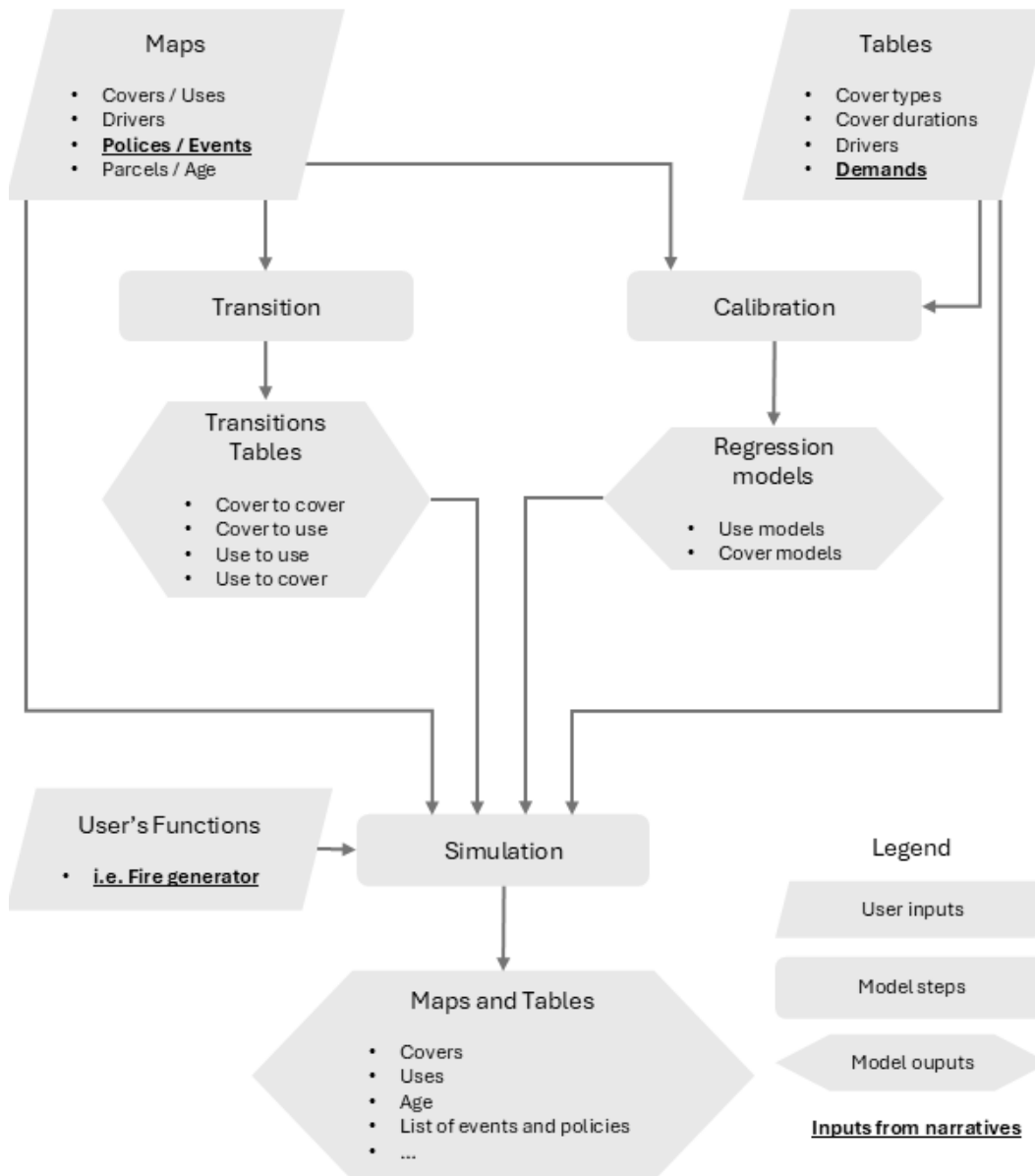
166 FORESCEM is built on a modular architecture that integrate all necessary processing components
 167 required to perform LUCC simulations—including transition, calibration, and simulation
 168 modules— while offering flexibility for users to customize the latter with their own functions
 169 (Figure 2).

170 *The Transition module* supports the definition of all land cover transitions based on two reference
 171 maps from different time points. When not explicitly defined by stakeholder narratives, future
 172 land-cover demand (i.e., the quantity of each land cover to be simulated) can be estimated using

173 a Markov Chain approach, similar to that employed in the Land Change Modeler (LCM) (Eastman,
174 2012). This module also assists users in identifying unrealistic or biologically implausible
175 transitions and in preparing the transition matrix for simulation. For example, a direct transition
176 from meadows to forest—though observed over a long interval—may be flagged if it omits
177 intermediate stages such as shrub encroachment, which are ecologically necessary for realism.
178 The *Calibration module* estimates the influence of spatially explicit drivers on the location of each
179 land cover. There is no predefined limit on the number of explanatory variables that can be used.
180 By default, logistic regression is employed to generate statistical models, which are then used to
181 compute probability maps as used by Verburg and Overmars (2007) and Mas et al. (2014). The
182 *Simulation module* loads all required inputs, including spatial masks, probability maps and policy
183 and event layers, and runs the simulation using user-defined functions. In this study, land cover
184 allocation is performed by selecting, for each parcel, the land cover type that maximizes the
185 computed probability while respecting the annual land demand and transition rules.

186 The simulation begins with an initialization phase during which all necessary data and
187 configuration parameters are loaded, including land cover, land use, parcel age, policy settings,
188 events, demand, and user-defined functions. The simulation then proceeds through a series of
189 iterations. Each iteration starts with the computation of target land areas based on current
190 demand and the previous system state. Subsequently, probability maps are generated for each
191 land cover and land use category. Next, various constraint masks are applied to adjust the
192 probability maps. The age mask enforces persistence or change according to parcel age. Land
193 cover and land use masks constrain possible transformations based on predefined transition
194 matrices. Policy masks weight the probabilities according to policy influence, while event masks
195 restrict potential changes to specific land covers and modulate demand accordingly. Following
196 the adjustment of probabilities, land cover allocations required to meet demand are determined.
197 This begins with non-competitive situations, where only one land cover is possible, followed by
198 competitive cases involving multiple candidates. Allocations not driven by demand are resolved
199 next. Land uses are then assigned. Finally, parcel ages are updated: they are reset to one if a
200 change has occurred or incremented by one if the parcel remains unchanged.

201 *Figure 2: FORESCEM architecture and functioning.*



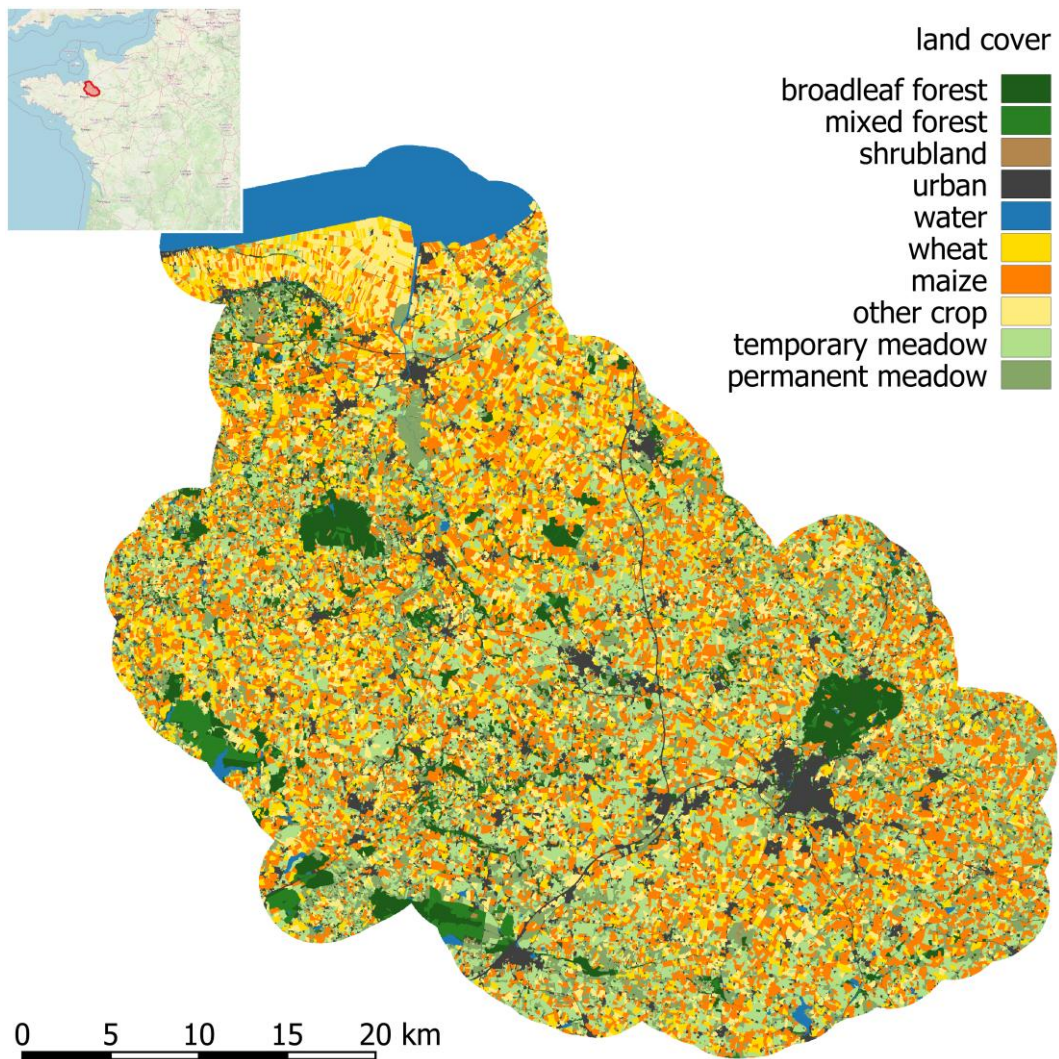
202

203 **2.2 Study sites**

204 The application and validation of FORESCEM were conducted using two contrasting study areas:
 205 the Couesnon catchment in Brittany, France, and the Pas, Miera, and Asón catchments in
 206 Cantabria, Spain. The French case study covers an area of 1,711 km², encompassing the
 207 Couesnon catchment itself along with a 3 km buffer zone (Figure 3). This region represents a highly
 208 anthropogenic landscape dominated by intensive agricultural land uses, particularly dairy and
 209 livestock production, which occupy approximately 80% of the study area. The predominant land
 210 covers include grasslands, maize, and wheat, arranged within a characteristic bocage landscape

211 (Baudry et al., 2000). Maize and wheat are typically found on flat or gently sloping areas with large
212 plots and deep soils, whereas grasslands are more commonly situated on granitic plateaus,
213 slopes with shallow soils, valley bottoms, or are integrated into crop rotations. Agricultural
214 intensity varies spatially: areas with higher densities of hedgerows, smaller plots, and a greater
215 prevalence of grasslands generally exhibit lower-intensity agricultural practices. In the northern
216 part of the catchment, adjacent to the coast, a polder zone is primarily used for cash crops and
217 vegetable production. Forestry activities are limited (covering ~8% of the area) and are mostly
218 confined to public forests. The principal urban center, Fougères, is a medium-sized town located
219 in the southeast of the catchment, with a population exceeding 50,000 inhabitants. Between 2006
220 and 2018, key land use trends included a significant expansion of urban areas (+2,300 ha) and a
221 slight reduction in agricultural land (-850 ha). Agricultural intensification was observed, marked
222 by an increase in crop-dominated areas (+3,100 ha, including +2,300 ha of maize) at the expense
223 of meadows (-4,000 ha). The Couesnon site offers a diverse set of conditions well-suited for
224 testing the capabilities of FORESCEM. These include highly heterogeneous land cover mosaics, a
225 wide range of land cover durations—from very short (1–2 years) to very long (>100 years)—and
226 varying spatial structures. These characteristics provide a robust context for evaluating the
227 model’s ability to represent complex landscape dynamics and simulate realistic land cover
228 trajectories.

229 *Figure 3: Presentation of the French anthropogenic case study: Land cover map of the Couesnon*
 230 *catchment in 2018.*



231

232 The Spanish case study covers an area of 2,958 km² and encompasses the Pas, Miera, and Asón

233 catchments, including their terrestrial, riverine, and estuarine components in the Cantabria

234 region. This area is further extended with a 3 km buffer (Figure 4). The northern coastal zone is

235 predominantly urbanized, interspersed with fragmented agricultural land uses. In contrast, the

236 southern portion of the study area is characterized by a semi-natural mountainous landscape,

237 with elevations exceeding 3,000m a.s.l. These high-altitude zones are primarily composed of bare

238 soil, grasslands, shrublands, and forests, and are subject to extensive pastoral activities and

239 frequent wildfires. Between these two extremes lies a hilly landscape consisting of a

240 heterogeneous mosaic of silvicultural plantations, unmanaged forests, shrublands, and

241 agricultural lands. This spatial heterogeneity, combined with dynamic ecological processes such

242 as vegetation succession and disturbance events (particularly wildfires), makes the region a

243 compelling case for LUCC modelling. Furthermore, land cover changes in this context are not

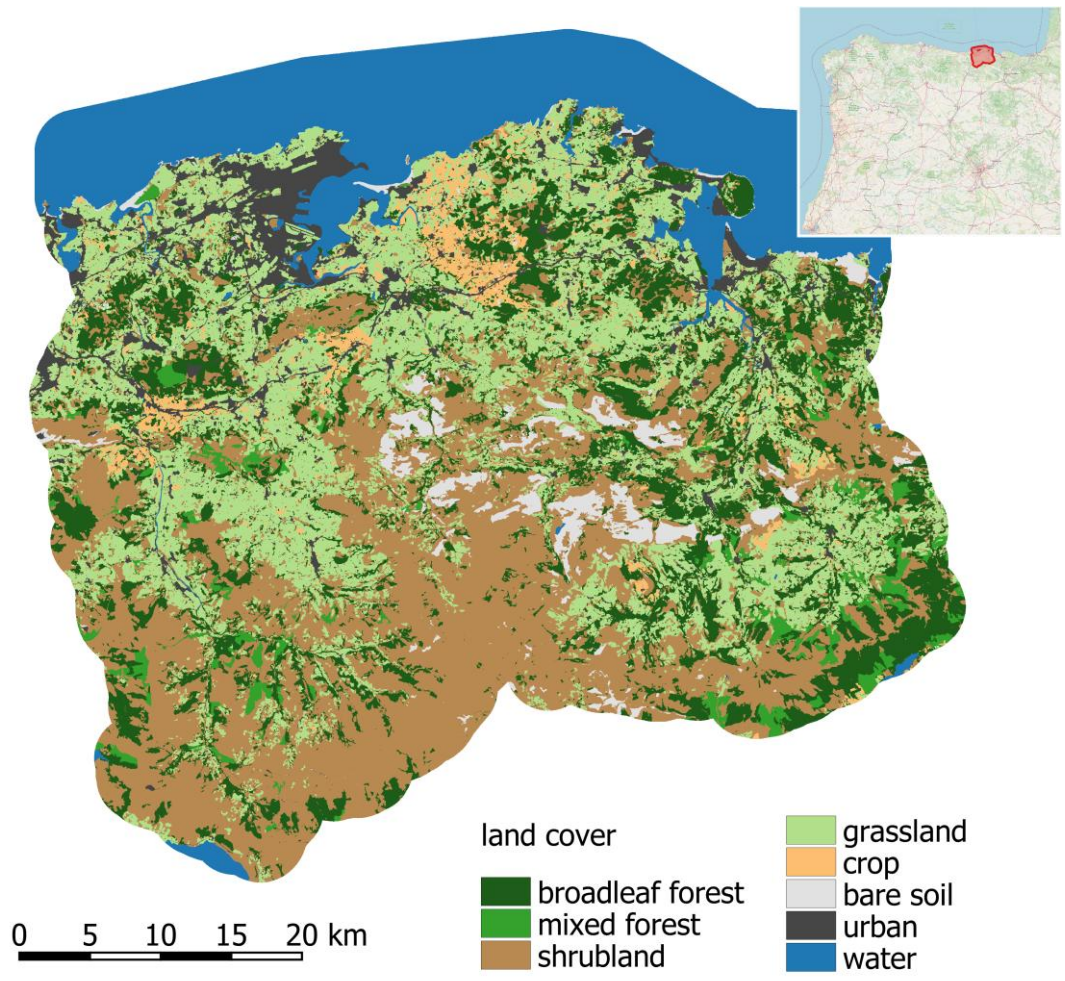
244 always confined to delineated landscape features such as cadastral parcels. Thus, integrating
245 such events is essential to ensure the representativeness and realism of the model outputs.
246 Observed land use trends between 2008 and 2018 include a modest increase in urban areas
247 (+148 ha) and a substantial decrease in agricultural land (-6,500 ha), primarily due to grassland
248 abandonment in the mountainous regions. These dynamics, driven by rural depopulation and
249 land abandonment, contribute to spontaneous reforestation processes that are often interrupted
250 or redirected by fire events. This study area offers valuable conditions for testing the FORESCEM
251 framework, particularly regarding: (1) Variable land cover durations, ranging from medium-term
252 (~5 years) to long-term (>100 years), which the model must accurately represent; and (2)
253 Disturbance-driven LUCC, where fire events act as exogenous drivers that disrupt natural
254 succession processes.

255 2.3 Dataset

256 2.3.1 List of input data for FORESCEM

257 FORESCEM needs a minimal input dataset to run simulations effectively. These include : two land
258 cover maps (at time t_n and t_0), two land use maps (at time t_n and t_0), a set of driver maps, an initial
259 age map for each land cover unit, a land cover duration table, a table linking drivers to land cover,
260 a table linking land covers to land uses, a land-cover priority table, and the annual land cover
261 demand. To support scenario customization and enhance simulation realism, several optional
262 inputs can also be integrated. These include updated drivers during the simulation period, event
263 and policy maps for land uses and land covers, parcels map (table 1). Additionally, other optional
264 data for customized land allocation functions can be added.

265 *Figure 4: Presentation of the Spanish case study: Land cover map of the Pas, Miera and Asón*
266 *watershed case study in 2018.*



267

268

269 *Table 1: Mandatory (M) and Optional (O) data in FORESCEM*

Data	Type	M/O	Description
Land cover at time t-n	Map	M	Land cover map used to compute past transitions, past trend, and the calibration
Land cover at time t	Map	M	Land cover map used to compute past transitions, past trend, and the calibration. It is also the starting landscape of the simulation
Land use at time t-n	Map	M	Land use map used to calibrate the model
Land use at time t	Map	M	Land use map as starting date of the simulation
Set of drivers	Maps	M	Maps used for the calibration and the simulation. Driver maps at time t+x can be included if drivers evolve during the simulation
Cover duration table	Table	M	Duration for each cover that FORESCEM will intend to respect. In some situations, cover duration can be exceeded to find a solution.
Cover type	Table	M	Table defining for each land cover if demand is a constraint or not.
Drivers	Table	M	Table to define which driver need to be used for the calibration for each land cover
Demand	Table	M	Table used during the simulation and gathering annual demand for each land cover
Parcels	Map	O	Simulation is processed at pixel unit if this map is not provided
Land cover's age at time t	Map	O	If no map is provided, a random age map respecting land cover duration is generated
Policy	Map	O	Map used to influence land allocation according to a narrative. It can be a hard (binary) or soft map. Policy is used from the year for which it is defined. For example, urban sprawl policy.
Event	Map	O	Map used to create unexpected change such as an urban project (housing estate, new lake), a forest project (new forest). It occurs from the date it is defined.

270

271 2.3.2 Data for the case studies

272 Land-cover maps were derived from remote sensing data. Multitemporal Sentinel-2 imagery was
 273 used to produce the 2018 land-cover maps for both study sites. For historical land cover data,
 274 multitemporal Landsat archives were employed: 1990 and 2006 for the French site, and 2008 for
 275 the Spanish site. Supervised random forest classification was applied to enhance vegetation
 276 discrimination, achieving overall accuracies (OA) exceeding 85% in each case. Subsequent post-
 277 processing, informed by local expert knowledge, was conducted to correct minor
 278 misclassifications—particularly those resulting from inconsistent transitions between land
 279 covers caused by spatial and temporal resolution differences between Sentinel-2 and Landsat
 280 datasets. Land-use maps were generated using validated land cover maps, supplemented by
 281 local expert input and ancillary geographical data, such as areas of exploited forests.

282 The LUCC drivers incorporated into the model include elevation, slope, aspect, geological
 283 characteristics, travel time to major cities, and land planning maps of the Blue and Green
 284 Infrastructure Network (BGIN). Elevation, slope, and aspect were derived from Digital Elevation

285 Models (DEMs), specifically the national BD ALTI 50 m dataset for France and the SRTM 90 m
286 dataset for Spain. Both DEMs were resampled to align with data consistency (10 x 10m).
287 Geological data were sourced from institutional databases and simplified to reduce the number
288 of geological classes. Travel time to major urban centers was calculated using OpenStreetMap
289 road network data. The BGIN maps, provided by local land planners, represent ecological
290 corridors with continuous values ranging from 0 (absence of corridor) to 1 (highest corridor
291 importance).

292 Five tables summarize key model inputs and parameters: (1) minimum and maximum land cover
293 duration, (2) drivers used for each land cover regression model, (3) drivers to be used for each land
294 use regression model, (4) annual land cover demands, (5) land cover types.

295 Landscape patterns are incorporated through the use of rasterized cadastral parcels for urban
296 and forested areas, and the Land Parcel Identification System (LPIS) parcels (data.europa.eu) for
297 agricultural lands. In mountainous regions or where parcel data are unavailable, homogeneous
298 units are derived by discretizing the landscape based on slope, elevation, and aspect classes.
299 These raster-based parcels aggregate contiguous 10 m resolution pixels that evolve as cohesive
300 units within the model. Employing parcels instead of individual pixels enhances the
301 representation of realistic landscape patterns in land change simulations (Sohl et al., 2017; Houet
302 et al., 2015). For the French and Spanish case studies, the parcel counts are approximately XX
303 and YY, respectively. All spatial data are pre-processed by aggregating values within each parcel.

304 2.4 Validation tests

305 The validation process is grounded on the premise that, given the inherent unpredictability of the
306 future, modelling efforts should primarily aim to maximize end-users' confidence in FORESCEM's
307 outputs. To achieve this, the validation tests are designed to demonstrate the model's capacity to
308 accurately reproduce historical LUCC and to incorporate policies and trend-breaking
309 assumptions present in future scenarios (Houet, 2014). Six distinct tests are conducted to do so.
310 The resulting simulations are benchmarked against a trend-based simulation calibrated on
311 observed LUCC data from 2006 to 2018 for France and from 2010 to 2018 for Spain. By applying
312 these tests across both study sites, the validation emphasizes FORESCEM's adaptive capability
313 in simulating diverse LUCC trajectories.

314 1) **Respecting landscape dynamics.** This test evaluates the model's ability to reproduce
315 historical LUCC dynamics. A simulation is conducted over the period 2006–2018 for the French
316 case study. The simulated land cover map is then compared to the observed classification derived

317 from remote sensing data. Model performance is quantified using the Figure of Merit (Pontius et
318 al., 2008) and Kappa indices as defined by van Vliet et al. (2011). (2011). Kappa, $\kappa_{\text{histogram}}$,
319 κ_{location} , $\kappa_{\text{simulation}}$, $\kappa_{\text{transition}}$, κ_{transloc} indicates respectively the similarity of the two
320 compared maps, the quantitative similarity of the two compared maps, the similarity of the spatial
321 allocation of the categories of the two compared maps, the similarity between simulated and real
322 transitions, the quantitative similarity between simulated and real transitions, and the similarity
323 of spatial allocation between simulated and real transitions. Analysis is made for all land cover
324 classes separately, and for all crops reclassified as a single class 'agricultural land' as crops
325 rotations show a high degree of randomness inheriting from individual farmers' decision.

326 2) **Respecting the duration of land covers.** This feature is particularly important for land
327 covers characterized by specific temporal dynamics, such as agricultural crop rotations. Most of
328 commonly used land change models are unable to accurately simulate these types of land cover
329 dynamics (Houet and Verburg, 2022). FORESCHEM's capacity to respect such constraints enables
330 the simulation of realistic agricultural practices. For example, in the French case study with an
331 intensive agricultural system, wheat cultivation is restricted to a maximum of two consecutive
332 years on the same plot. Maize cultivation generally does not (1) exceed three consecutive years
333 and (2) typically follows wheat. Temporary meadows have durations ranging from one to seven
334 years. However, under certain conditions, the full set of constraints—including land use
335 duration—may result in no feasible solution that satisfies all constraints simultaneously. In these
336 cases, FORESCHEM is designed to override the duration constraints to ensure the model can find
337 a viable solution.

338 3) **Simulating unexpected land cover transitions resulting from land use changes.** Land
339 development projects, such as afforestation initiatives, can drive land cover changes that are not
340 predicted by historical trends. To simulate such scenarios, a new silvicultural zone is introduced
341 in 2028 in the French case study, without prior information on expected land cover changes.
342 FORESCHEM is designed to enforce these unexpected land cover transitions triggered by land use
343 changes defined as events in the stakeholder narratives, while striving to maintain the overall
344 proportions of initial land cover demand. For instance, transitions initially prohibited—such as
345 from wheat land cover to recolonization land cover—are allowed to occur. Subsequently, the
346 recolonization land cover progresses to forest cover after 10 years, as dictated by the configured
347 land cover duration parameters.

348 4) **Simulating variations in land cover demands.** Compared to historical trends, a
349 substantial shift in crop demand is anticipated following a reform of the Common Agricultural
350 Policy. Based on a narrative simulating this policy shift in 2026, which triggers agricultural
351 intensification, this test examines a marked increase in wheat and maize at the expense of

352 grasslands and other crops. During the calibration period, the respective annual increases for
353 wheat and maize were +25.6 ha and +192.5 ha. Post-2026, these rates are projected to rise to
354 +43.2 ha and +496.5 ha per year, respectively.

355 5) **Simulating trend-breaking policies.** Urban planning policies evolve over time. For
356 instance, the French urban management plan, defined at the municipal level, is expected to
357 become more restrictive in the future to limit artificialization. This test evaluates how the
358 FORESCEM framework responds when areas previously designated as suitable for urban
359 development become temporarily unavailable due to policy restrictions, and are later reopened
360 following local policy changes. Specifically, it assesses how the model handles annual urban land
361 demand when no suitable areas are available during a certain period, but new areas become
362 accessible later.

363 6) **Including case-specific land change patterns.** Countries experiencing warm and dry
364 summers are prone to recurrent fires caused by natural hazards or human activities. In the
365 Spanish case study, fires frequently occur in mountainous areas, significantly affecting land cover
366 changes such as afforestation. To address this, a module generating random fire events from past
367 events is added in the FORESCEM framework to demonstrate its ability to integrate specific rules
368 / modules adapted to specific case studies. The module analyzes, prior to the start of the
369 simulation and based on historical fire records, both the frequency of fire occurrences on each
370 plot and the fire size distribution. In the Spanish case study, fire recurrence is annual, thus one
371 fire map is produced per year. During each step of the simulation, the module incorporates a pre-
372 solver with specific land-use assignment rules (e.g., forced transition to one-year-old shrubland
373 or to bare soil, thereby limiting shrubland recolonization).

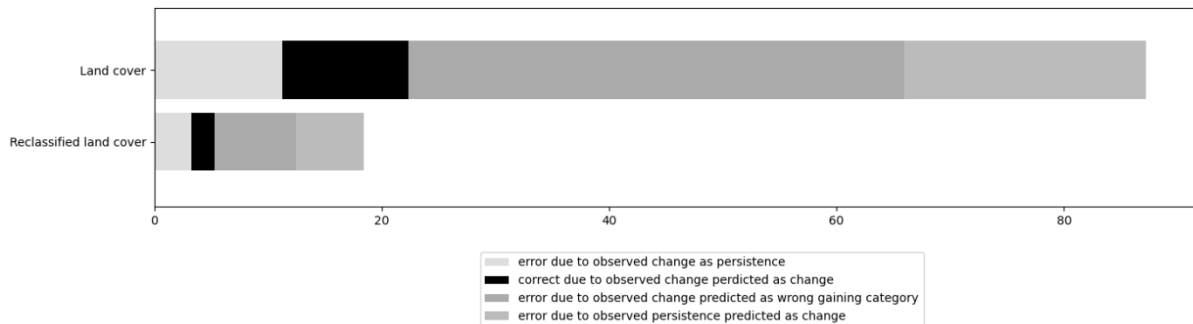
374 3 Results

375 3.1 Respecting landscape patterns

376 The simulated map exhibits some differences when compared to the observed map derived from
377 remote sensing (Figure A in annexe). While the Figure of Merit and Kappa indices highlight these
378 discrepancies, the Similarity and Quantity indices indicate that the overall landscape pattern
379 remains reasonably consistent with observed conditions. The Figure of Merit, which is based on
380 the proportion of correctly predicted changes relative to all predicted and observed changes
381 (Figure 5), reaches 12.7% for the simulation, compared to 24.44% for the null model (i.e.,
382 assuming no change). When agricultural land covers involved in crop rotations are aggregated into

383 a single class, the Figure of Merit decreases to 11.15% for the simulation and increases to 32.38%
 384 for the null model.

385 *Figure 5: Figure of merit*



386

387 The kappa index shows a rather low correspondence ($\text{kappa} = 0.35$) when all classes are
 388 considered (Table 2). This low value is due to crop rotations (Table 3). Grouping the covers involved
 389 in crop rotations (wheat, maize, other crop, and temporary meadow) into a single class leads to a
 390 higher kappa value ($\text{kappa} = 0.80$). The similarity indicators for quantities and locations are also
 391 high ($\text{kappa}_{\text{histogram}} = 0.95$ and $\text{kappa}_{\text{location}} = 0.84$ respectively). Moreover, if we look more
 392 specifically at the similarities between simulated and real transitions the values remain very high
 393 ($\text{kappa}_{\text{simulation}} = 0.81$; $\text{kappa}_{\text{transition}} = 0.92$ and $\text{kappa}_{\text{transloc}} = 0.88$).

394 *Table2: Kappa indices considering all land cover class (first column) and reclassified land cover*
 395 *(agricultural, forest, urban, water classes)*

Index	Meaning	Land cover	Reclassified cover
Kappa	similarity of the two compared maps	0,35	0,80
Kappa _{histogram}	quantitative similarity of the two compared maps	0,95	0,95
Kappa _{location}	similarity of the spatial allocation of the categories of the two compared maps	0,37	0,84
Kappa _{simulation}	similarity between simulated and real transitions	0,42	0,81
Kappa _{transition}	quantitative similarity between simulated and real transitions	0,82	0,92
Kappa _{transloc}	similarity of spatial allocation between simulated and real transitions	0,51	0,88

396

397

398 *Table 3: Kappa index per land cover*

Land cover	kappa		Reclassified land cover
Broadleaf forest	0,92	0,92	Broadleaf forest
Mixed forest	0,83	0,83	Mixed forest
Shrubland	0,06	0,06	Shrubland
Water	1,00	1,00	Water
Urban	0,87	0,87	Urban
Wheat	0,09	0,61	Land covers as part of crops' rotations
Maize	0,14		
Other crop	0,08		
Temporary meadow	0,13		
Permanent meadow	0,61	0,86	Permanent meadow

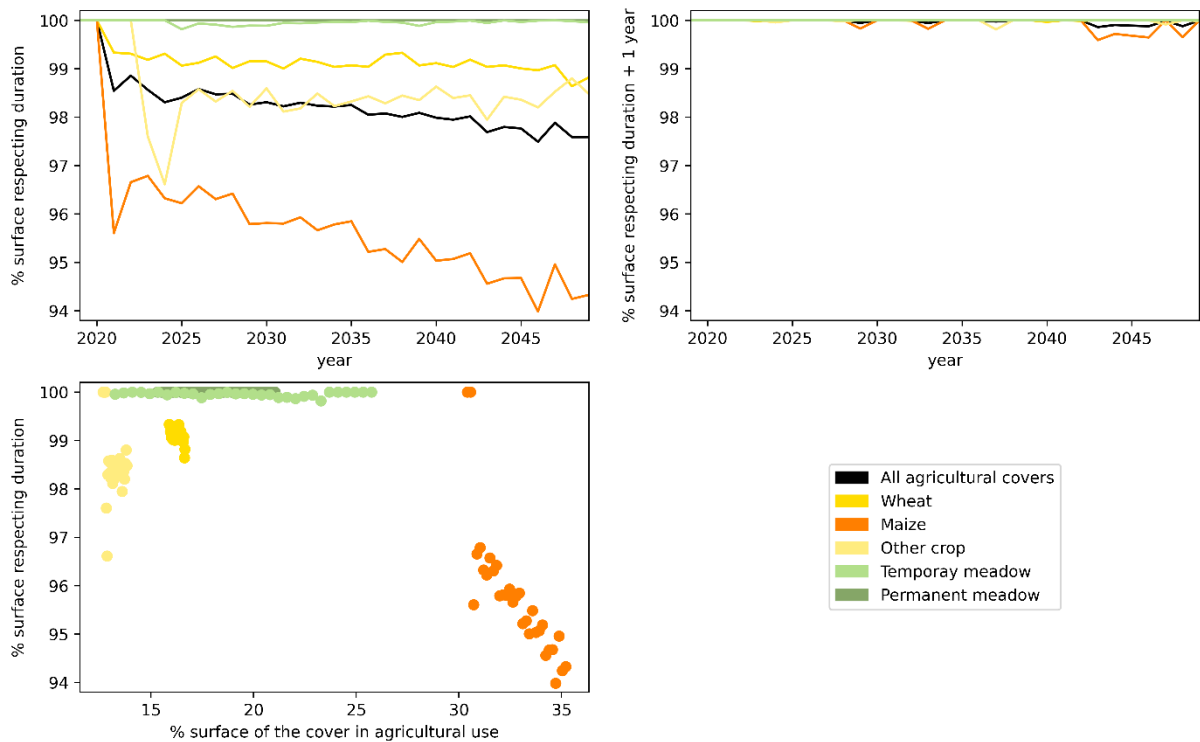
399

400 **3.2 Respecting the duration of land covers: Crop occurrences /**
 401 **maximum duration**

402 We focus here on agricultural land covers—wheat, maize, other crops, permanent and temporary
 403 meadows—that exhibit specific temporal dynamics, including varying durations and frequencies
 404 of occurrence. Results demonstrate that FORESCEM successfully respects land cover duration in
 405 most cases (>98% for all agricultural land covers; Figure 6, top left and bottom left). Less than
 406 2.5% of the total agricultural area exceeds the maximum duration threshold, while still meeting
 407 overall land cover demand. This level of non-compliance is particularly limited for temporary
 408 meadows (under 0.03% of their total area), wheat (less than 1%), and other crops (less than 2%).
 409 For maize, which accounts for more than 30% of the agricultural land use at the initial time step
 410 and over 35% by the final year, 3–6% of the area surpasses the three-year duration limit. However,
 411 in practice, maize can be cultivated on the same plot annually for 10 to 15 years in certain
 412 locations. This observed deviation highlights the influence of diverse and localized agricultural
 413 practices, which are challenging to model precisely. In essence, the generalization and
 414 simplification of land cover change rules in FORESCEM can explain some of the localized
 415 discrepancies. The shorter the maximum allowed duration, the more difficult it becomes for the
 416 model to reconcile this constraint with annual agricultural land cover demands. For other crops,
 417 non-compliance is mainly concentrated in a specific region—namely, the polder areas north of
 418 Couesnon catchment—where pedological conditions favour more frequent transitions between
 419 wheat and other crops such as vegetables and orchards. When the duration threshold is relaxed

420 by one year (e.g., allowing wheat to be maintained for up to four years), overall non-compliance
 421 drops to just 0.1% of the total agricultural area. The highest rate of non-compliance under this
 422 scenario is observed for wheat, reaching only 0.4% in the year 2043 (Figure 6, top right). This
 423 indicates that most violations stem from minor extensions in crop duration to maintain optimal
 424 land use efficiency on the most suitable soils.

425 *Figure 6: proportion of crops respecting duration*



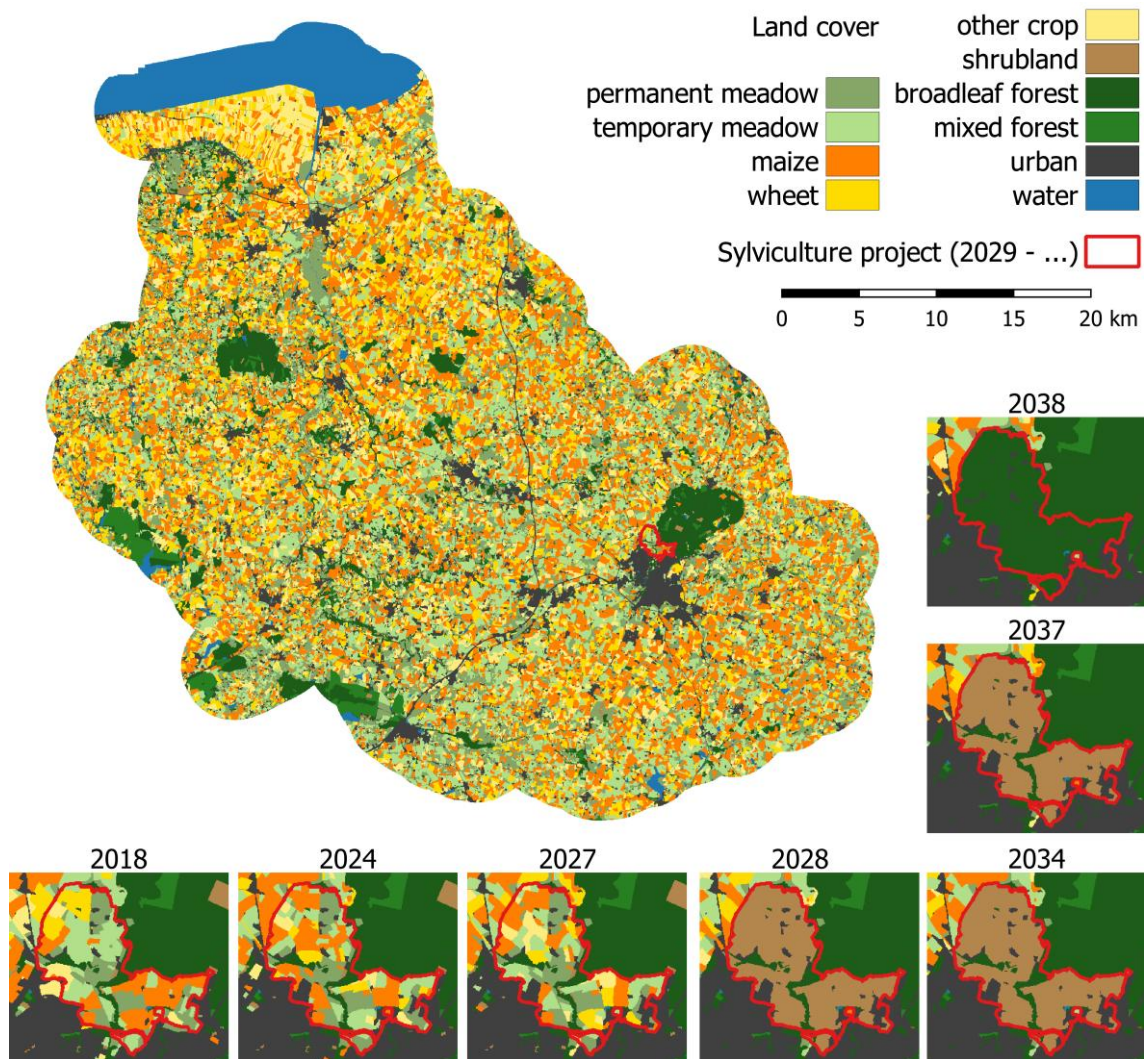
426

427 3.3 Simulating unexpected land cover transitions resulting from land 428 use changes: influence of an event

429 Figure 7 illustrates a scenario-based silvicultural project initiated in 2028. Prior to this
 430 intervention, urban sprawl and agricultural land cover changes follow their usual patterns.
 431 However, once the silvicultural land use project begins, urban expansion halts, and selected
 432 agricultural land covers are converted to shrubland—representing areas planted with young trees.
 433 In this scenario, a specific event triggers a local shift in land cover dynamics: for example, maize
 434 cultivated in 2027 transitions directly to shrubland in 2028, bypassing typical transitions such as
 435 grassland or wheat. This illustrates FORESCEM’s ability to override predefined constraints in the
 436 transition matrix when necessary to accommodate scenario-based land use changes. The model

437 adapts to event-driven shifts in land cover by prioritizing narrative-defined land-use objectives,
 438 demonstrating its flexibility and responsiveness to local planning decisions.

439 *Figure 7: Land cover in 2018 and land cover changes in and out the sylvicultural project area that*
 440 *occurs in 2028*



441

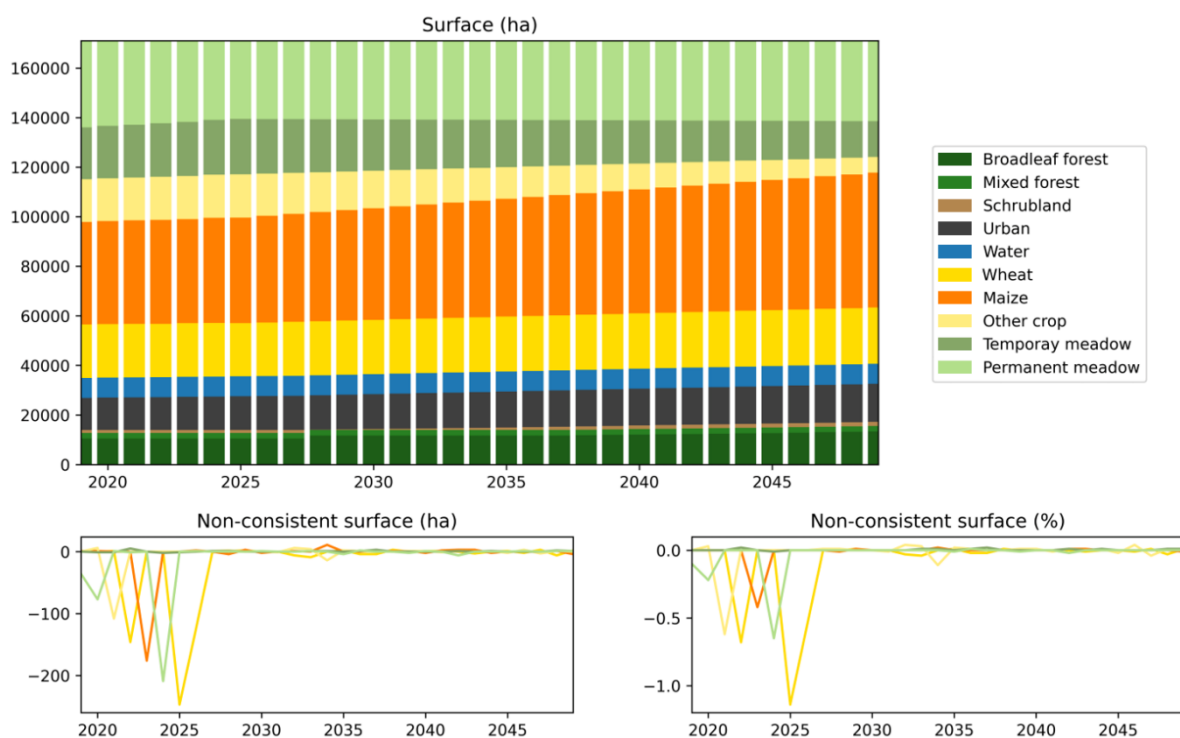
442

443 3.4 Simulating variations in land cover demands

444 Figure 8 shows that the evolution of agricultural land covers aligns well with the land cover
 445 demand changes introduced in 2026. Maize surfaces increase significantly, while wheat expands
 446 at a more moderate rate. In contrast, areas covered by other crops and permanent meadows
 447 experience a notable decline. The model adheres closely to the specified demand, with a
 448 maximum deviation of only 246 hectares—equivalent to 1.13% of the total study area—between
 449 simulated and expected land cover surfaces. These discrepancies are largely attributed to crop

450 rotation constraints. At the beginning of the simulation, the initial age of all land covers is
 451 arbitrarily set to one year. During the first seven years—matching the maximum duration allowed
 452 for permanent meadows—land cover options remain limited due to uniform age distributions and
 453 competition between covers. Beyond this period, the diversification of land cover ages across
 454 parcels reduces these constraints, enabling greater flexibility to meet the demand. However,
 455 minor variations persist due to the influence of parcel size, as illustrated in the lower graphs of
 456 Figure 8.

457 *Figure 8: Land-cover change with change in agricultural demand. On the left, land-cover surface.*
 458 *On the top-right, difference between simulated and expected agricultural surfaces. On the*
 459 *bottom-right, percentage of the surface difference related to the expected agricultural surface.*



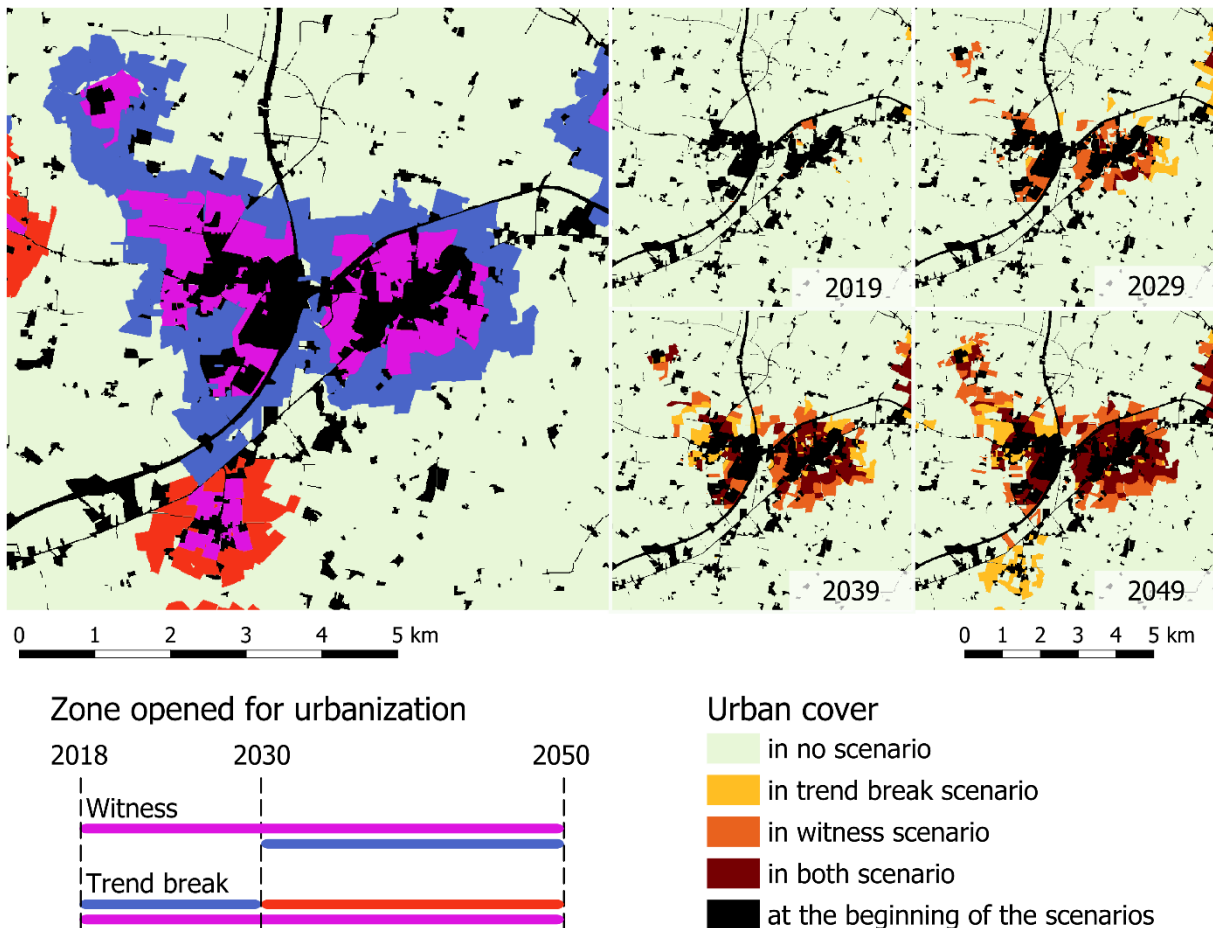
460

461 3.5 Simulating trend-breaking policies

462 Figure 9 illustrates the impact of changing urbanization policies in a municipality. In the witness
 463 scenario, areas in purple are open from 2018 to 2050 and areas in blue are open for urban
 464 development from 2030 to 2050. In the trend-breaking scenario, where urban policy evolves,
 465 purple areas remain also open to urbanization from 2018 to 2050, blue areas become restricted
 466 after 2030, and red areas are newly opened to compensate for the closures. These red areas are
 467 located in municipalities that have become more attractive due to proximity to a major
 468 transportation axis. This test demonstrates FORESCEM’s ability to manage spatial policy changes

469 (opening and closing accessible areas) and resolve land use conflicts. It ensures that new urban
 470 development does not occur in unauthorized areas while distinguishing between pre-existing
 471 urban land cover and potential expansion areas—urban sprawl typically occurs adjacent to
 472 existing urban zones. Moreover, this example reinforces FORESCEM’s capability to handle
 473 complex policy-driven dynamics. By relying on the land use–land cover relationship table and the
 474 transition matrix, the model determines which land cover transitions are allowed based on the
 475 current land use and policy context of each parcel. This distinction allows FORESCEM to simulate
 476 realistic policy impacts on land development patterns.

477 *Figure 9: Urban sprawl in 2019, 2029, 2039 and 2049. On left, areas open to urbanization for the*
 478 *witness scenario (purple from 2018 to 2029, then purple and blue from 2030 to 2025) and trend-*
 479 *breaking scenario (purple and blue from 2018 to 2029, then purple and red from 2030 to 2050). On*
 480 *the right, comparison of urbanized areas between the witness and trend-breaking scenarios.*



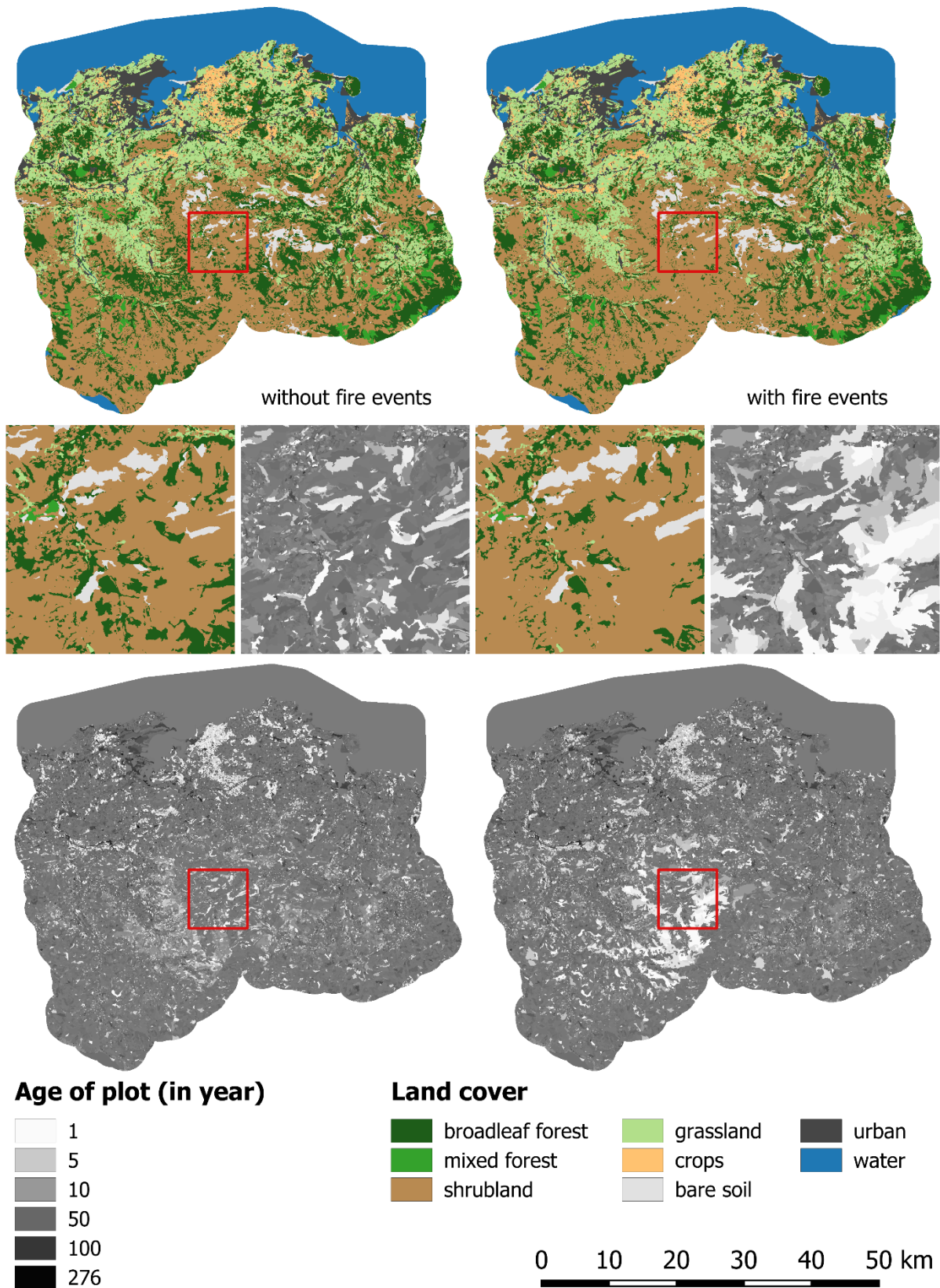
481

482 **3.6 Case-specific land change patterns: accounting for fire events**

483 Fires in Spain do not appear to have had a significant impact on overall land cover during the
 484 simulation period (Figure 10). However, while fire events may not drastically alter land cover

485 classes, they do influence the age of parcels, which is reset to zero following a burn event. In the
486 Spanish case study, simulated fires produce localized effects with subtle land cover transitions.
487 Specifically, they facilitate the conversion from shrubland to bare soil, while limiting the natural
488 succession from bare soil to shrubland and from shrubland to forest. As a result, fire disturbances
489 contribute to maintaining open landscapes in mountainous areas, aligning with the persistence
490 of traditional pastoral land-use practices.

491 *Figure 10: Land cover and age in 2050 without fire event (on the left) and with fire events (on the*
 492 *right).*



493

494 4 Discussion

495 Simulating future land use and land cover changes (LUCC) based on narratives requires
496 anticipating a wide range of possible changes. Many of these changes cannot be validated against
497 past data, as they are speculative or unprecedented. At the same time, relying too heavily on past
498 trends for calibration may overly constrain the model, limiting its ability to explore and simulate
499 contrasting future scenarios. A robust model must therefore strike a balance: it should be capable
500 of handling exploratory, narrative-based simulations while also producing business-as-usual
501 scenarios calibrated on observed LUCC, assuming a stationary system—an approach commonly
502 adopted in many existing LUCC models (Mas et al., 2014). In this context, two central issues are
503 discussed in the paper: (1) The characteristics and functionalities of the model implemented
504 within the FORESCEM framework and (2) the validation process of a LUCC model in the context of
505 future land planning.

506 4.1 Characteristics of FORESCEM for future land planning

507 FORESCEM introduces several key advancements in the modelling and simulation of land use
508 and land cover changes (LUCC). These include: (1) The ability to simulate changes at a fine spatial
509 resolution, enabling a detailed representation of landscape patterns and their temporal
510 dynamics; (2) A clear distinction between land use and land cover, along with explicit modelling
511 of their interactions and dependencies; (3) The capacity to easily incorporate policies and
512 scenario-based events, such as afforestation projects or non-linear urban development
513 trajectories; (3) The integration of complementary, case-specific modules that allow adaptation
514 to local contexts and narrative-driven assumptions. Together, these features make FORESCEM
515 well-suited for supporting and simulating spatially explicit, contrasting prospective scenarios, as
516 emphasized by Houet et al. (2022).

517 Furthermore, the use of parcel-based elementary units strengthens the model's capacity to
518 preserve key landscape structures in scenario outcomes. As shown by Houet et al. (2015) and
519 Sohl et al. (2017), parcel-based modelling not only provides a more realistic depiction of the
520 spatial heterogeneity and organization of land cover classes, but also enhances downstream
521 applications such as biodiversity assessments based on land cover maps.

522 Differentiating land use and land cover processes and dynamics enhances both the flexibility and
523 genericity of FORESCEM when constructing a wide range of scenarios. From a modelling
524 perspective, it avoids the need to multiply land cover types to represent every possible transition.
525 Instead, FORESCEM maintains a consistent logic of land cover transitions while modulating them

526 according to the land use context. For instance, it distinguishes shrublands resulting from
527 agricultural abandonment from shrublands established as part of a forestry land use. The model
528 further incorporates other spatial parameters, such as landscape units or soil quality (treated as
529 sub-regions), to authorize or restrict specific transitions or to locally modulate land cover
530 duration. This design reduces the burden of converting stakeholder and expert knowledge into a
531 large number of complex transition rules. Instead, stakeholders can focus on defining scenario
532 assumptions, which are then translated into land use or land cover change rules via event or
533 policy layers, or transition matrices. This approach highlights the importance of involving the
534 modeller early in the scenario co-construction process, working closely with stakeholders to
535 ensure that assumptions are accurately and meaningfully translated into simulation parameters
536 and spatial rules. FORESCEM's ability to easily incorporate policy changes, unexpected events,
537 or narrative-driven developments makes it well suited to support a wide spectrum of future
538 scenarios. As described by the IPBES (IPBES, 2016), this flexibility supports the co-construction
539 of exploratory, target-seeking or policy-screening scenarios. Even within exploratory contexts,
540 scenario assumptions may define desired landscape compositions, include nature-based
541 solutions, or evaluate the effectiveness of landscape projects (e.g., enhancing connectivity or
542 biodiversity). FORESCEM's structure allows some inputs to remain loosely defined, facilitating
543 iterative dialogue with stakeholders and enabling the model to adapt to local needs and
544 knowledge.

545 The FORESCEM framework combines parameterized yet generic sub-models, built on core
546 mandatory modules—calibration, transitions, and simulation—with optional functions that can
547 be developed and integrated based on the specific case study. This adaptability and its explicit
548 treatment of land use–land cover interactions make FORESCEM particularly effective for
549 modelling fine-scale, prospective scenarios in highly anthropogenic landscapes. Crucially,
550 FORESCEM accommodates two types of dynamics often found in real-world systems: (1) Trend-
551 based changes, following gradual and often predictable evolutions (e.g., urban expansion or land
552 abandonment), and (2) Abrupt changes, triggered by events or decisions such as policy shifts,
553 land reclassification, or natural hazards (e.g., wildfires or floods).

554 As Hersperger et al. (2018) point out, spatial planning operates under both progressive
555 transformations and sudden deviations from past trends. This duality exists in urban contexts and
556 in natural systems—such as the rapid designation of protected areas. As emphasized by Koomen
557 et al. (2011), the capacity to accommodate diverse planning and land management approaches
558 is essential. FORESCEM's structure meets this need, making it a versatile tool for LUCM modelling
559 in support of integrated, participatory, and adaptive spatial planning.

560 Nonetheless, FORESCEM has some limitations. As revealed by conventional land change
561 modelling metrics, its spatial allocations occasionally diverge from observed patterns. Enhancing
562 the model's ability to better preserve landscape structure remains a challenge. One promising
563 direction is to incorporate intermediate organizational levels—such as farms, municipalities, or
564 inter-municipal groupings—to improve the simulation of landscape patterns and dynamics.
565 However, the availability and accessibility of detailed data on these units, particularly farm
566 boundaries, remain challenging, independent from FORESCEM.

567 4.2 How validating LUC models when combined with prospective 568 scenarios?

569 The validation of land change models typically relies on metrics such as the ROC curve, AUC, or
570 Kappa index (van Vliet et al., 2016). However, these indicators can be challenging to apply in
571 certain contexts, especially for prospective scenarios. This difficulty arises from the
572 fundamentally different paradigms underlying land change modelling versus scenario-building.
573 While traditional modelling strives for predictive accuracy, the prospective approach recognizes
574 that the future is inherently uncertain and may follow multiple possible trajectories.
575 Consequently, scenarios cannot be validated solely based on prediction accuracy but rather
576 through criteria such as relevance, transparency, creativity, plausibility, and consistency. A land
577 change model designed to simulate future narratives—where predictive validation is
578 impossible—does not fit within current validation standards. Nonetheless, model calibration
579 remains a critical step with strong implications for the model's capacity to simulate contrasted,
580 trend-breaking scenarios. FORESCEM thus contributes to shifting the validation paradigm in land
581 change science, complementing the predictive approach by emphasizing flexibility and scenario
582 relevance.

583 To address this challenge, we propose a combination of commonly used validation approaches
584 aimed at increasing end-user confidence in the model's outputs and capabilities. Some tests
585 assess the model's ability to reproduce known past dynamics and quantify the similarity between
586 simulated and observed landscapes. Others evaluate whether the model can fulfill stakeholder
587 requirements and constraints, including evolving ones like minimum land use durations. A final
588 category of tests examines the model's capacity to simulate abrupt shifts triggered by specific
589 projects (e.g., forestry or urban development), policy changes (e.g., urban expansion restrictions),
590 or external events (e.g., wildfires). This validation approach complements conventional unitary
591 tests and indices. We therefore advocate for applying such a comprehensive approach to land
592 change models designed to simulate contrasted, participatory narratives. To our knowledge, most

593 existing land change model literature has focused on predictive validation methods, which raises
594 questions about their suitability for simulating disruptive scenarios—including anthropogenic
595 projects, temporal inversions or variations in land demand relative to past trends, and new drivers
596 influencing land change allocation.

597 Furthermore, when working at fine spatial scales, simulations become increasingly sensitive to
598 data availability and the spatial representation of outcomes. For example, access to past urban
599 planning documents and information on intermediate organizational levels—such as farms or
600 municipalities—can significantly influence land dynamics. These factors directly impact the
601 model’s predictive performance and its ability to simulate realistic land change dynamics and
602 patterns, which in turn affects end-user confidence. Crop rotation modelling illustrates this
603 complexity, as it depends on parameters like initial crop age, minimum and maximum rotation
604 durations, multiple possible land cover transitions, and farm boundaries—data that are often
605 difficult to obtain. Consequently, this can lead to variations during the simulation period and
606 result in lower scores on standard performance indicators, even when the landscape
607 composition, spatial configuration, and dynamics are accurately represented at the case study
608 scale.

609 Beyond functional validation tests, local stakeholders’ expertise plays a crucial role in prospective
610 modelling. While local actors pay close attention to the model’s ability to respect predefined
611 constraints, the plausibility of the simulated dynamics—especially given their inherent
612 uncertainty—strongly influences stakeholder acceptance and the perceived relevance of the
613 results. Stakeholders typically prioritize the model’s capacity to realistically simulate the spatial
614 allocation and dynamics of land use and land cover. Notably, FORESCEM’s spatially explicit
615 outcomes have never been challenged by stakeholders, whereas certain scenario assumptions
616 (such as urban land demand) were questioned and subsequently adjusted to enhance
617 stakeholder confidence and engagement, as documented in Houet et al. (2022).

618 5 Conclusion

619 This paper presents the FORESCEM scenario-based LUCM modelling framework. Its innovative
620 strength lies in its ability to simulate interactions between land use and land cover changes, while
621 accounting for different land planning processes. These processes can influence both land use
622 and land cover through gradual land planning policies or sudden land development projects. The
623 simulation considers two types of interactions between land use and land cover: (1) direct

624 interactions, where a land use change drives land cover changes, and (2) indirect interactions,
625 where land cover acts as a driving factor for land use changes—for example, land abandonment.
626 The validation focused on the key mechanisms of the FORESCEM modelling framework that
627 enable it to capture interactions and diverse processes embedded in narratives. Each mechanism
628 was validated through unitary tests conducted with local stakeholders and experts, assessing
629 their ability to reproduce the expected scenario-based changes. This validation approach also
630 challenges conventional methods commonly used in land change science. When simulating
631 prospective scenarios, the validation paradigm shifts from evaluating predictive accuracy toward
632 assessing the model’s capacity to simulate realistic land patterns and dynamics. This aligns with
633 the perspective of Burgi et al. (2022), who advocate rethinking determinant analysis and
634 emphasize the importance of validating land change models in collaboration with local
635 stakeholders.

636 References

- 637 Akber, M. A., Khan, M. W. R., Islam, M. A., Rahman, M. M., & Rahman, M. R. (2018). Impact of land
638 use change on ecosystem services of southwest coastal Bangladesh. *Journal of land use*
639 *science*, 13(3), 238-250.
- 640 Albert, C., Fürst, C., Ring, I., & Sandström, C. (2020). Research note: Spatial planning in Europe
641 and Central Asia—Enhancing the consideration of biodiversity and ecosystem services.
642 *Landscape and Urban Planning*, 196, 103741.
- 643 Alcamo. J. (2008). The SAS approach: combining qualitative and quantitative knowledge in
644 environmental scenarios. In: Alcamo J (ed), *Environmental Futures: the Practice of*
645 *Environmental Scenario Analysis*, Elsevier, Amsterdam, pp 123–150
- 646 Bartha, S., Campetella, G., Canullo, R., Bódis, J., & Mucina, L. (2004). On the importance of fine-
647 scale spatial complexity in vegetation restoration studies. *International Journal of Ecology*
648 *and Environmental Sciences*, 30(1), 101-116.
- 649 Baudry, J., Bunce, R.G.H., Burel, F., 2000. Hedgerows: an international perspective on their origin,
650 function and management. *J. Environ. Manage.* 60, 7–22.
- 651 Bürgi, M., Celio, E., Diogo, V., Hersperger, A. M., Kizos, T., Lieskovsky, J., ... & Verburg, P. H. (2022).
652 Advancing the study of driving forces of landscape change. *Journal of Land Use Science*,
653 17(1), 540-555.

654 Cihlar, J., & Jansen, L. J. (2001). From land cover to land use: a methodology for efficient land use
655 mapping over large areas. *The Professional Geographer*, 53(2), 275-289.

656 Couclelis, H. (2005). "Where has the future gone?" Rethinking the role of integrated land-use
657 models in spatial planning. *Environment and planning A*, 37(8), 1353-1371.

658 Curt, T., Marsteau. C., Michalland, B., Prevosto, B. (1998). Dynamique et gestion des boisements
659 spontanés de moyenne montagne, Gip ECOFOR / Cemagref.

660 Delheimer, M. S., Moriarty, K. M., Munro, H. L., Early, D. A., Hamm, K. A., & Green, R. E. (2023).
661 Structural complexity characterizes fine-scale forest conditions used by Pacific martens.
662 *The Journal of Wildlife Management*, 87(4), e22388.

663 Dorning, M. A., Koch, J., Shoemaker, D. A., & Meentemeyer, R. K. (2015). Simulating urbanization
664 scenarios reveals tradeoffs between conservation planning strategies. *Landscape and
665 Urban Planning*, 136, 28-39.

666 Edman, T., Angelstam, P., Mikusiński, G., Roberge, J. M., & Sikora, A. (2011). Spatial planning for
667 biodiversity conservation: assessment of forest landscapes' conservation value using
668 umbrella species requirements in Poland. *Landscape and urban planning*, 102(1), 16-23.

669 Eastman R (2012) Idrisi Selva, Guide to GIS and Image Processing, manual version 17.01, Clark
670 University, Worcester, MA, USA. p 324.

671 Godet, M., (1986). Introduction to la prospective: seven key ideas and one scenario method.
672 *Futures*, vol. 18, p. 134-157

673 Güneralp, B., Reilly, M. K., & Seto, K. C. (2012). Capturing multiscalar feedbacks in urban land
674 change: a coupled system dynamics spatial logistic approach. *Environment and Planning
675 B: Planning and Design*, 39(5), 858-879.

676 Hersperger, A. M., Oliveira, E., Pagliarin, S., Palka, G., Verburg, P., Bolliger, J., & Grădinaru, S.
677 (2018). Urban land-use change: The role of strategic spatial planning. *Global Environmental
678 Change*, 51, 32-42.

678 Houet T. (2014), How validating future LUCC based on scenario-based modeling approach?.
679 Global Land Project open science meeting: Land transformations: between global
680 challenges and local realities. 23-25 mars, Berlin, Allemagne. (Poster)
681 <https://hal.science/hal-04666243>

682 Houet, T., Grémont, M., Vacquié, L., Forget, Y., Marrioti, A., Friconnet, B., Bourrier, F., Puissant, A.,
683 Peltier, A., Bernardie, S., Thiery, Y., Vandromme, R., Grandjean, G., (2017). Downscaling

684 scenarios of future LUC using a participatory approach: an application to mountain risk
685 assessment, *Regional Environmental Change*, pp 1-15. doi: :10.1007/s10113-017-1171-z

686 Houet, T., Marchadier, C., Bretagne, G., Moine, M. P., Aguejdad, R., Viguie, V., ... & Masson, V.
687 (2016). Combining narratives and modelling approaches to simulate fine scale and long-
688 term urban growth scenarios for climate adaptation. *Environmental Modelling & Software*,
689 86, 1-13.

690 Houet, T., Aguejdad, R., Doukari, O., Battaia, G., & Clarke, K. (2016). Description and validation of
691 a “non path-dependent” model for projecting contrasting urban growth futures. *Cybergeo:*
692 *European Journal of Geography*.

693 Houet T., Vacquié L., Sheeren D., (2015) Evaluating the spatial uncertainty of future land
694 abandonment in a mountainous valley (Vicdessos, Pyrenees - France): insights from model
695 parameterization and experiments. *Journal of Mountain Science*, 12(5), 1095-1112,
696 <http://dx.doi.org/10.1007/s11629-014-3404-7>

697 Houet, T., Schaller, N., Castets, M., Gaucherel, C., (2014). Improving the simulation of fine scale
698 landscape changes coupling top-down and bottom-up land use and cover changes rules.
699 *International Journal of Geographical Science*. 28(9), 1848-1876,
700 <http://dx.doi.org/10.1080/13658816.2014.900775>

701 Houet, T., & Verburg, P. H. (2022). Exploring futures in landscape agronomy: methodological
702 issues and prospects of combining scenarios and spatially explicit models. In *Landscape*
703 *Agronomy* (pp. 163-181). Springer, Cham.

704 IPBES (2016): The methodological assessment report on scenarios and models of biodiversity and
705 ecosystem services. S. Ferrier, K. N. Ninan, P. Leadley, R. Alkemade, L. A. Acosta, H. R.
706 Akçakaya, L. Brotons, W. W. L. Cheung, V. Christensen, K. A. Harhash, J. Kabubo-Mariara,
707 C. Lundquist, M. Obersteiner, H. M. Pereira, G. Peterson, R. Pichs-Madruga, N.
708 Ravindranath, C. Rondinini and B. A. Wintle (eds.). Secretariat of the Intergovernmental
709 Science-Policy Platform on Biodiversity and Ecosystem Services, Bonn, Germany. 348
710 pages.

711 Koomen, E., Koekoek, A., & Dijk, E. (2011). Simulating land-use change in a regional planning
712 context. *Applied spatial analysis and policy*, 4(4), 223-247.

713 Laiolo, P., Dondero, F., Ciliento, E., & Rolando, A. (2004). Consequences of pastoral abandonment
714 for the structure and diversity of the alpine avifauna. *Journal of Applied Ecology*, 41(2), 294-
715 304.

716 Lambin, E. F., & Geist, H. J. (Eds.). (2008). *Land-use and land-cover change: local processes and*
717 *global impacts*. Springer Science & Business Media.

718 Mas J F, Kolb M, Paegelow M, Camacho Olmedo M T, Houet T (2014) Modeling Land use / cover
719 changes: a comparison of conceptual approaches and softwares. *Environmental Modelling*
720 *and Software*, 51:94-111

721 Mertens, B., & Lambin, E. (1999). Modelling land cover dynamics: integration of fine-scale land
722 cover data with landscape attributes. *International Journal of Applied Earth Observation*
723 *and Geoinformation*, 1(1), 48-52.

724 Mottet A, Ladet S, Coqué N, Gibon A (2006) Agricultural land-use change and its drivers in
725 mountain landscapes: A case study in the Pyrenees. *Agriculture, Ecosystems and*
726 *Environment*, 114:296–310

727 Pontius R G, Boersma W, Castella J C, Clarke K, de Nijs T, Dietzel C, ... & Verburg P H (2008)
728 Comparing the input, output, and validation maps for several models of land change. *The*
729 *Annals of Regional Science*, 42, 11-37.

730 Poyatos R, Latron J, Llorens P (2003) Land use and land cover change after agricultural
731 abandonment - the case of a Mediterranean mountain area (Catalan pre-Pyrenees).
732 *Mountain Research and Development*, 23:362–368

733 Rigo R, & Houet T (2023) Do Land Use and Land Cover Scenarios Support More Integrated Land
734 Use Management?. *Land*, 12(7), 1414

735 Rigo R, Martin P, Verburg P H, Houet T (2022) Contributions of local LUCC spatially explicit
736 scenarios for water management: Lessons learned from an ex-post evaluation. *Futures*,
737 139, 102937

738 Silva, E., & Wu, N. (2012). Surveying models in urban land studies. *Journal of Planning Literature*,
739 27(2), 139-152.

740 Sohl T, Dornbierer J, Wika S, Sayler K, Quenzer R (2017). Parcels versus pixels: modeling
741 agricultural land use across broad geographic regions using parcel-based field boundaries.
742 *Journal of Land Use Science*, 12(4), 197-217.

743 UNEP (2002) Global Environment Outlook 3, Nairobi, Kenya, UNEP

744 van Vliet J, Bregt A K, & Hagen-Zanker A (2011) Revisiting Kappa to account for change in the
745 accuracy assessment of land-use change models. *Ecological modelling*, 222(8), 1367-
746 1375.

747 van Vliet J, Bregt A K, Brown D G, van Delden H, Heckbert S, Verburg P H (2016), A review of current
748 calibration and validation practices in land change modeling, *Environmental Modelling and
749 Software*, 82:174-182

750 Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: current
751 practice and research priorities. *GeoJournal*, 61(4), 309-324.

752 Verburg, P. H. (2006). Simulating feedbacks in land use and land cover change models. *Landscape
753 Ecology*, 21(8), 1171-1183.

754 Verburg P H, Rounsevell M, Veldkamp A (2006), Scenario-based studies of future land use in
755 Europe. *Agriculture, Ecosystems and Environment*, 114(1):1-6

756 Verburg P H, Dearing J A, Dyke J G, van der Leeuw S, Seitzinger S, Steffen W, Syvitski J (2016)
757 Methods and approaches to modelling the Anthropocene. *Global Environmental Change*.
758 39:328-340 doi: 10.1016/j.gloenvcha.2015.08.007

759 Verburg, P. H., & Overmars, K. P. (2007). Dynamic simulation of land-use change trajectories with
760 the CLUE-s model. In *Modelling land-use change* (pp. 321-337). Springer, Dordrecht.

761 Wang, X. (2001). Integrating water-quality management and land-use planning in a watershed
762 context. *Journal of environmental management*, 61(1), 25-36.

763 Wilson, E., & Piper, J. (2008). Spatial planning for biodiversity in Europe's changing climate.
764 *European Environment*, 18(3), 135-151.

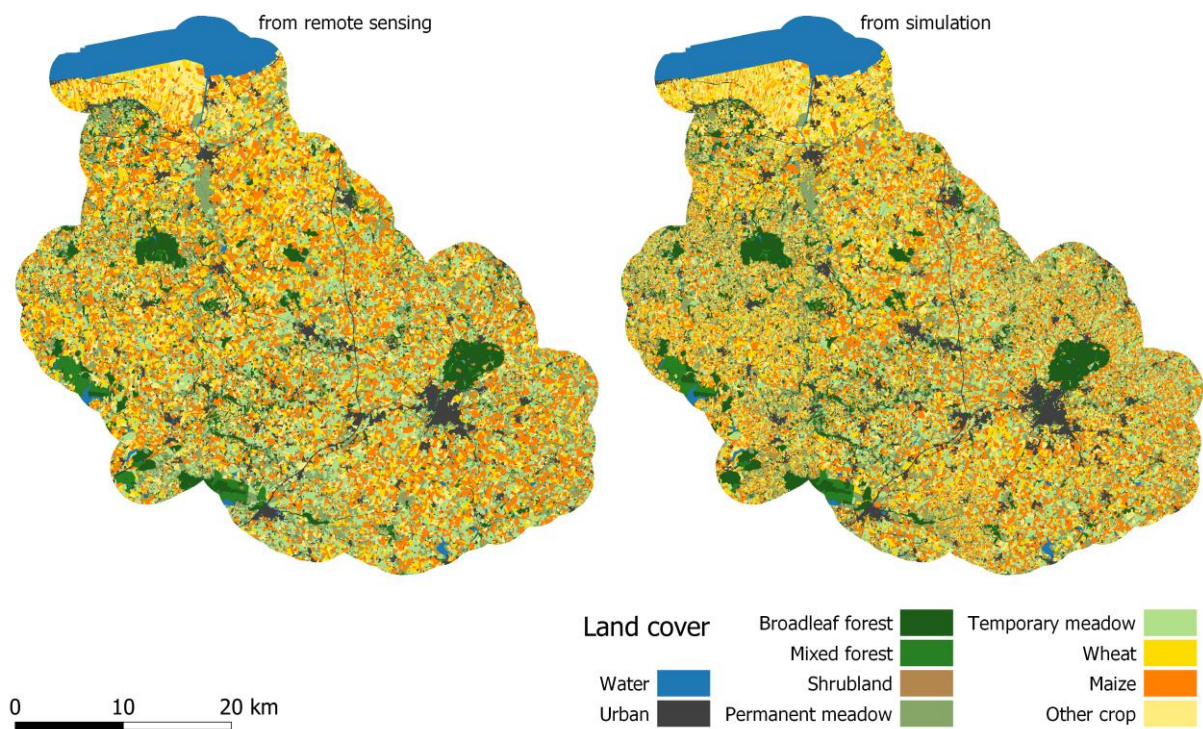
765 Xiang, W. N., & Clarke, K. C. (2003). The use of scenarios in land-use planning. *Environment and
766 planning B: planning and design*, 30(6), 885-909.

767

768 **Annexe**

769 Figure A illustrates these results: although agricultural land covers are not allocated exactly as
770 expected, the overall landscape pattern remains consistent. One key limitation is that FORESCEM
771 does not currently account for intermediate organizational levels such as farms or municipalities,
772 which hinders finer-scale allocation of land covers. As highlighted by Houet et al. (2014),
773 modelling medium- to long-term crop rotations remains a complex task and is not yet predictive.
774 Some discrepancies may also stem from differences in input data sources. The 2006 map was
775 derived from Landsat 8 imagery with a 30 m resolution, whereas the 2018 map uses Sentinel-2
776 data at 10 m resolution. This difference results in the appearance of many small built structures
777 in 2018 that were either absent or undetected in earlier imagery. In the case of the urban class, it
778 becomes particularly difficult to distinguish between actual new developments around existing
779 settlements and previously undetected buildings.

780 *Figure A: Land cover in 2018 from remote sensing (left) and from simulation (right)*



781

782