

1 **Representing anthropogenic gross land use change, wood harvest and forest**
2 **age dynamics in a global vegetation model ORCHIDEE-MICT v8.4.2**

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17
18 **Abstract**

19 Land use change (LUC) is among the main anthropogenic disturbances in the global carbon cycle. Here
20 we present the model developments in a global dynamic vegetation model ORCHIDEE-MICT v8.4.2 for
21 a more realistic representation of LUC processes. First, we included gross land use change (primarily
22 shifting cultivation) and forest wood harvest in addition to net land use change. Second, we included sub-
23 grid even-aged land cohorts to represent secondary forests and to keep track of the transient stage of
24 agricultural lands since LUC. Combination of these two features allows simulating shifting cultivation
25 with a rotation length involving mainly secondary forests instead of primary ones. Furthermore, a set of
26 decision rules regarding the land cohorts to be targeted in different LUC processes have been
27 implemented. Idealized site-scale simulation has been performed for miombo woodlands in Southern
28 Africa assuming an annual land turnover rate of 5% grid cell area between forest and cropland. The result
29 shows that the model can correctly represent forest recovery and cohorts aging arising from agricultural
30 abandonment. Such a land turnover process, even though without a net change in land cover, yields
31 carbon emissions largely due to the imbalance between the fast release from forest clearing and the slow
32 uptake from agricultural abandonment. The simulation with sub-grid land cohorts gives lower emissions
33 than without, mainly because the cleared secondary forests have a lower biomass carbon stock than the

34 mature forests that are otherwise cleared when sub-grid land cohorts are not considered. Over the region
35 of Southern Africa, the model is able to account for changes in different forest cohort areas along with the
36 historical changes in different LUC activities, including regrowth of old forests when LUC area
37 decreases. Our developments provide possibilities to account for continental or global forest demographic
38 change resulting from past anthropogenic and natural disturbances.

39

40 Keywords: dynamic vegetation model, gross land use change, age dynamics, shifting cultivation, wood
41 harvest, land use emissions

42

43 **1 Introduction**

44 Land use and land use change (LUC) strongly modifies the properties of the Earth's surface, ecosystem
45 services and the carbon and nutrient fluxes between the land and the atmosphere. These activities have
46 significant impacts on the Earth's climate through both biogeochemical and biophysical effects (Foley et
47 al., 2005; Luysaert et al., 2014; Mahmood et al., 2014). When a forest is cleared, the majority of carbon
48 stored in the aboveground biomass is lost as CO₂ to the atmosphere. Such loss can occur within a few
49 years if fire is used in deforestation (Morton et al., 2008), or more slowly through decomposition of the
50 slash left on the ground (Houghton, 1999). Various products made from harvested wood, though, often
51 take a few decades to degrade and return the carbon to the atmosphere (Mason Earles et al., 2012). In
52 addition, LUC changes the balance between litter input and heterotrophic respiration, resulting in changes
53 in soil organic carbon (SOC) (Don et al., 2011; Guo and Gifford, 2002; Poelau et al., 2011; Powers et
54 al., 2011).

55

56 Globally, LUC activities have contributed significantly to historical anthropogenic carbon emissions. It is
57 estimated that about 800 Mha (1Mha = 10⁶ha) of forests were cleared for agricultural purpose and that
58 2000 Mha of forests were harvested during 1850–1999, giving rise to cumulative emissions of 124 Pg C,
59 or 33% of the total anthropogenic emissions (Houghton, 1999). Houghton et al. (2012) reviewed LUC
60 emissions from multiple studies and estimated the annual global LUC emissions as 1.1 Pg C yr⁻¹ during
61 1980–2009, with an uncertainty of 0.5 Pg C yr⁻¹. Different estimations of historical LUC emissions by
62 Dynamic Global Vegetation Models (DGVM) show a spread as large as 1 Pg C yr⁻¹ (see Fig. 1 in
63 Houghton et al. 2012; see also Hansis et al. 2015 for an even larger range among model estimations). This
64 is partly due to different forcing data used and initial carbon stocks simulated (Li et al., 2017), but also
65 because of different implementations of LUC processes in dynamic global vegetation models (Prestele et
66 al., 2016). Given the importance of understanding historical LUC emissions in projecting the future land-

67 based mitigation potential, a more realistic representation of LUC processes and land management in
68 DGVMs is desirable.

69

70 In most global studies, only net transitions were accounted for in the LUC processes simulated by
71 DGVMs (Le Quéré et al., 2015). Changes in land use over each model grid cell are diagnosed as the
72 difference in ground fractions of different land cover types between two consecutive years. At a typical
73 spatial resolution of 0.5° for global applications (e.g., TRENDY, Sitch et al., 2015; MsTMIP,
74 http://nacp.ornl.gov/MsTMIP_simulations.shtml), such a scheme has ignored the simultaneous, bi-
75 directional transitions between two vegetation types within the same grid cell (i.e., gross transitions).
76 Such gross transitions can arise from spatial upscaling of land use change data, or from certain land use
77 activities. A typical example is shifting cultivation, a form of smallholder subsistence agriculture
78 primarily occurring in tropical regions that involves clearing a forest for a non-permanent agricultural
79 land, which is often abandoned later. Shifting cultivation was historically important in many tropical
80 regions for the subsistence of indigenous people (Hurt et al., 2011; Lanly, 1985) although more recently
81 it has been in the process of being superseded by more intensified land management (Heinimann et al.,
82 2017). Forest management such as a clear-cut for wood harvest followed by replanting trees is another
83 type of gross transition. Although it does not entail any net change in land cover (forest remaining forest),
84 species choice and forest management can have a significant effect on carbon stocks and fluxes (Erb et
85 al., 2017).

86

87 More and more DGVMs started to include gross transitions and we provide an overview of them in Table
88 1. All models in Table 1 include shifting cultivation and wood harvest except that shifting cultivation is
89 not included in ISAM, and five of them include sub-grid secondary land tiles when accounting for land
90 use change. A recent review by Arneth et al. (2017) found that including processes that have been
91 previously neglected in DGVMs, including gross transitions and other land management processes such
92 as crop harvest and management, can lead to an upward shift of estimated LUC emissions. Their study
93 thus highlights the importance of including these processes. Furthermore, to more robustly account for
94 shifting cultivation and wood harvest, which often have a certain rotation length and mainly involve
95 secondary forests of different ages, it is critical for DGVMs to include sub-grid differently aged land
96 cohorts. This feature exists in some DGVMs that combine with a forest gap model (e.g., LPJ-GUESS,
97 Bayer et al., 2017) but it would be difficult to represent forest species change because different tree plant
98 functional types are mixed over a model grid cell. The same also applies for LM3V (Shevliakova et al.,
99 2009). Other so-called area-based DGVMs (Smith et al., 2001) such as ISAM (Jain et al., 2013) and LPX-
100 Bern 1.0 (Stocker et al., 2014) included secondary land tiles in the model but their capability to represent

101 different rotation lengths in land use is limited. In the ORCHIDEE model, sub-grid forest cohorts have
102 been recently included in the ORCHIDEE-CAN branch mainly for forest management purposes (Naudts
103 et al., 2015), but to combine both sub-grid land demography and gross land transition is still missing.
104

105 Here we present the new model developments in ORCHIDEE that combines both sub-grid land cohorts
106 and gross land use change. The objectives of this study are: (1) to document a new LUC module,
107 including sub-grid vegetation cohorts, forest harvest and gross land use change in the ORCHIDEE model,
108 that can be run with and without sub-grid age dynamics; (2) to document through an idealized pixel
109 simulation the simulated carbon fluxes from shifting cultivation or land turnover between model set-ups
110 with and without sub-grid age dynamics; and (3) to document the model behaviour and forest age
111 dynamics associated with the historical changes in LUC activities. Whereas the current manuscript
112 focuses on documenting new model developments and subsequent changes in model behaviour, a
113 companion paper presents a global re-analysis of historical LUC emissions (Yue et al., 2017).

114 **2 Methods**

115 **2.1 Model developments to include sub-grid vegetation cohorts and gross transitions**

116 **2.1.1 Original land use change module with net transitions only**

117 The model version as the starting point for our development is ORCHIDEE-MICT (r3247), a branch of
118 the ORCHIDEE DGVM (the major version is called the trunk version), the land surface component of
119 the French IPSL Earth System Model (ESM). ORCHIDEE can simulate the energy, water and carbon
120 fluxes between the land surface and the atmosphere. The carbon module simulates vegetation carbon
121 cycle processes, including photosynthesis, photosynthates allocation, vegetation mortality and
122 recruitment, phenology, litter fall and soil carbon decomposition. ORCHIDEE-MICT is a branch initially
123 focusing on improving high-latitude processes (e.g., soil freezing, snow processes, permafrost dynamics
124 and northern wetlands) but is now under development to include more processes. Of interest for this study
125 is that the grassland management module developed in Chang et al. (2013) is included (r2615). This
126 allows for distinction between natural grassland and pasture that have been mixed together in previous
127 LUC simulations by ORCHIDEE.
128

129 In ORCHIDEE, land cover types are represented as plant functional types (PFTs), with each PFT being
130 associated with a set of parameters. A typical model simulation consists of two stages: a spin-up stage
131 with stable or constant forcing data until the model reaches an approximately equilibrium state, to mimic
132 an era with no appreciable human perturbation, and a transient stage, where the model is forced with
133 temporally varying forcings (e.g., climate, atmospheric CO₂, land cover etc.). The land use change

134 module prior to this study accounts for net transitions only (Piao et al., 2009a) and has been used in many
135 applications (e.g., CMIP5, <http://icmc.ipsl.fr/index.php/cmip5>; TRENDY, Sitch et al., 2015). To simulate
136 historical land use change, a spin-up run is initiated with a given initial land cover map (i.e., a PFT map),
137 and then vegetation distribution is updated annually with prescribed PFT map time series during the
138 transient simulation. The LUC module simply compares grid cell fractions of different PFTs between the
139 current simulation year and the next year. Then twelve vegetative PFTs (all standard model PFTs
140 excluding the bare soil PFT) are separated into two groups with expanding versus contracting areas.
141 Carbon stocks and associated carbon fluxes on shrinking PFTs are displaced to expanding PFTs in
142 proportion to their respective surface increments.

143 **2.1.2 Concept of gross transitions in relation to vegetation age structure**

144 The numerical implementation of net transitions is straightforward. However, as explained in the
145 introduction, this scheme omits important sub-grid gross land use transitions. Figure 1 uses an exemplary
146 grid cell to illustrate the difference between the two LUC schemes: one accounting for net transitions only
147 (Fig. 1b), and the other accounting for gross transitions but with no sub-grid cohorts (Fig. 1c & 1d).
148 Although the areas of forest and cropland after LUC are identical (Fig. 1b & 1d), carbon stocks for the
149 same vegetation type (e.g., forest) are different between the two schemes. According to the net transition
150 scheme, the carbon stock of the final forest patch shown in Fig. 1b remains intact. But under the gross
151 scheme (Fig. 1d), the post-LUC forest carbon stock is an area-weighted mean between the original forest
152 patch not being impacted by LUC, and the newly established forest with a low carbon density that results
153 from cropland abandonment. Consequently the carbon stock of the grid cell is expected to be smaller in
154 Fig. 1d than in 1b and LUC carbon emission in Fig. 1d is conversely larger than in 1b.

155
156 Figure 1c represents the real land cover state after LUC, while the merging shown in Fig. 1d is only a
157 necessary simplification when no sub-grid cohorts are represented in the model. Ideally, the model
158 capability could be expanded to include cohorts, to represent the real world case as in Fig. 1c. In addition,
159 inclusion of sub-grid cohorts would allow not only the distinction between original intact forest and
160 newly established forest, but also allow distinguishing among different forest cohorts (e.g., primary
161 versus secondary forests) regarding which forest patch to be cleared for cropland.

162
163 Figure 2 illustrates a case where gross LUC is combined with sub-grid cohort representation in the model.
164 Here, multiple patches within a grid cell are used to represent cohorts of a single vegetation type but with
165 different ages since establishment. These cohorts often have different carbon stocks either due to different
166 lengths in carbon accumulation time (e.g., for forest) or due to different extents to which legacy soil
167 carbon is present (e.g., for croplands establishing on former forests). The areas subject to gross LUC

168 transition in Fig. 2a & 2b remain the same as in Fig. 1a (dashed red rectangles), but primary and
169 secondary forests are cleared in Fig. 2a and Fig. 2b, respectively. Thus LUC emissions from clearing of
170 primary forest are expected to be higher due to its higher biomass stock. Correspondingly, the legacy soil
171 carbon stocks on the cohort of new cropland are also higher (shown in Fig. 2b & 2d).

172

173 Figure 1 and Fig. 2 have shown the example of LUC transitions between forest and cropland, but other
174 types of land use changes, including forest harvest, can be handled in a similar way. In the case of forest
175 harvest, having cohorts avoids the simplification to merge a young re-established forest after harvest with
176 the original forest, which serves as the exact source of harvest. This can effectively simulate forest
177 management practices that induce rotations of different forest cohorts (e.g., see McGrath et al., 2015 for a
178 forest management history in Europe).

179 **2.1.3 Expansion of ORCHIDEE-MICT capability to represent sub-grid vegetation cohorts**

180 In order to simulate gross LUC combined with sub-grid vegetation cohorts as illustrated in Fig. 2, we
181 expanded the ORCHIDEE-MICT capability to include sub-grid even-aged cohorts. This necessitates
182 multiple patches within a grid cell for a single PFT, which inherit most of the parameters from their
183 parent PFT (they still belong to the same PFT and thus are largely physically similar). These patches are
184 named here *Cohort Functional Types (CFT)*, to be distinguished from the original *plant functional types*.
185 In this sense, the original PFTs actually become “meta-PFTs” which were named meta-classes (MTCs).
186 As subsequent land use changes generate differently aged CFTs, the computational demand will be
187 greatly increased. Hence, the number of CFTs within an MTC is limited to a user-defined number.

188

189 ORCHIDEE-trunk has a feature called “PFT externalization” which allows creating a user-specified new
190 PFT by inheriting its parameters from an existing one. A user can then modify specific parameters at their
191 convenience. Based on this feature, the ORCHIDEE-CAN branch (svn rev. = r2566; Naudts et al., 2015,
192 Page 2037) has developed representation of sub-grid forest age classes (i.e., equivalent to our CFTs here).
193 Each forest age class is an inheritance of a given forest MTC. There, the transitions from one age class to
194 another were defined by tree diameters. When a forest of a certain age class reaches its diameter limit, it
195 moves into the next age class, and is merged with the existing forest patch of that age class if there is one.
196 All associated biophysical and biogeochemical variables are merged as well following an area-weighted
197 mean approach with a few exceptions for discrete variables such as the applied forest management
198 strategy.

199

200 ORCHIDEE-MICT also inherits this “externalization” feature from ORCHIDEE-trunk. Here we ported
201 the codes of forest age class functionality from ORCHIDEE-CAN to develop the CFT functionality

202 needed for LUC simulation with cohorts in ORCHIDEE-MICT. The code base to include sub-grid forest
203 cohorts were migrated from ORCHIDEE-CAN, with substantial adaptations being made in ORCHIDEE-
204 MICT. Except for this, all other LUC developments have been achieved within the current study.
205 Contrary to ORCHIDEE-CAN (see above), ORCHIDEE-MICT uses woody biomass to delimit different
206 forest cohorts, with older cohorts having a higher woody biomass. Forest grows old by moving from the
207 current cohort to the next one when the woody biomass exceeds the cohort upper boundary. Except for
208 the cohort boundaries, no further cohort-specific parameterizations have been done, so essentially all
209 cohorts are governed by the same set of biophysical and ecological parameter values. However, in
210 ORCHIDEE-MICT there are indeed some simple “aging” processes to approximate the key changes when a
211 forest grows old, notably, the NPP allocation to belowground sapwood decreases with the time since
212 establishment.

213
214 In addition, we expanded the concept of CFT to croplands, natural grasslands and pastures. Cohorts are
215 defined with their soil carbon stocks for these herbaceous vegetation types; this is a definition relevant to
216 LUC emission calculation. Because the directional change of soil carbon largely depends on the
217 vegetation types before and after LUC and on climate conditions (Don et al., 2011; Poeplau et al., 2011),
218 ideally agricultural cohorts from different origins should be differentiated. However, to avoid inflating the
219 total number of cohorts and the associated computation demand, as a first attempt, we simply divide each
220 herbaceous MTC into two broad sub-grid cohorts according to their soil carbon stocks and without
221 considering their individual origins. We expect that such a parameterization can accommodate some
222 typical LUC processes, such as the conversion of forest to cropland where soil carbon usually decreases
223 with time, but not all LUC types (for instance, soil carbon stock increases when a forest is converted to a
224 pasture). The biomass or soil carbon thresholds that delineate different CFTs must be properly
225 parameterized in order to have sensible CFT segregation within different contexts of land use change.
226 This will be further detailed in the Sect 2.2.3. In practice, for single-site simulations, the parameterization
227 could be set up via a configuration file enumerating the thresholds for all CFTs. For regional applications,
228 an input file containing spatially explicit thresholds will be used.

229
230 The implementation of sub-grid cohort function types as inheritances of meta-classes and the
231 corresponding hierarchy are exhibited in Fig. 3a. “Tier 1” of the “*Model parameterization hierarchy*”
232 corresponds to the four basic vegetation types (forest, natural grassland, pasture, and croplands,
233 abbreviated as *f*, *g*, *p*, *c* respectively). “Tier 2” corresponds to meta-classes in ORCHIDEE-MICT, which
234 contain one bare soil MTC and fourteen vegetative MTCs, with each vegetative MTC belonging to one of
235 the four basic vegetation types. “Tier 3” corresponds to cohort function types. A cohort functional type is

236 noted as $CFT_{i,j}$ to denote that it inherits its parameter values from the MTC_i and belongs to the j^{th} cohort.
237 For this study, forest MTCs contain six CFTs and herbaceous MTCs contain two CFTs. The number of
238 CFTs for each MTC is not hard-coded in the model and can be specified by users via a configuration file.

239
240 With sub-grid cohorts, the model spin-up run is initiated with an input MTC map, essentially the same as
241 in the case without sub-grid cohorts (recall that in Sect. 2.1.1 this MTC map is called a PFT map). But the
242 difference is that the initial prescribed areas (as fractions of grid cell area) of different MTCs are all
243 assigned to their youngest cohorts. During model spin-up forest woody mass will grow to exceed the
244 thresholds of the first cohort, so that forests will move to the second cohort, and so on. At the end of spin-
245 up, all forests thus end up in the oldest cohort of each MTC. The same case applies to herbaceous MTCs,
246 given that cohort thresholds are properly defined (see more details in Sect. 2.2.3).

247
248 Natural forest mortality in ORCHIDEE could be either prescribed as a constant rate or dynamically
249 simulated, but in the case of prescribed vegetation cover, mortality takes effects by reducing the amount
250 of existing biomass only, with the coverage of the concerned forest patch being unchanged. Likewise,
251 recruitment increases forest individual density and update leaf age and other relevant variables, but again,
252 forest coverage remains unchanged. These features are necessary, as the original ORCHIDEE model does
253 not take into account forest demography. As explained in Krinner et al. (2015, page 8), recruitment
254 sapling biomass is only incorporated when the existing biomasses is virtually zero while a larger-than-
255 zero ground coverage is prescribed. These features remain the same when sub-grid cohorts are used, i.e.,
256 forest mortality or recruitment does not modify forest cohort ground coverage. In addition, forest
257 mortality and subsequent regeneration due to forest fires are handled in a similar manner. ORCHIDEE-
258 MICT has integrated a prognostic fire module to simulate open grassland and forest fires arising from
259 both natural and anthropogenic ignitions (Yue et al., 2014). Other forest disturbances, such as wind-
260 throw, diseases and insect outbreaks, are not explicitly considered in ORCHIDEE-MICT. Because of
261 these reasons, after the spin-up, the only way to create secondary cohorts in the model is through land use
262 change.

263
264 When entering transient simulations with land use change, younger cohorts will begin to be created. From
265 a modeling perspective, the oldest cohorts in ORCHIDEE-MICT are somewhat equivalent to the
266 primary lands (especially, the oldest forest cohorts are equivalent to primary forests), and other younger
267 cohorts are analogue to secondary lands.

268 **2.1.4 Model developments to include gross land use change and forest harvest, with and without**
269 **sub-grid cohorts**

270 This section describes the implementation of gross land use change and forest harvest with sub-grid
271 CFTs. We focus on the implementation with sub-grid cohorts, because the same LUC process without
272 cohorts could be simply treated as a particular case where all MTCs have only one single cohort. The
273 module interface is designed to receive forcing information on land area fluxes among four basic land
274 cover types of forest (*f*), natural grassland (*g*), pasture (*p*) and cropland (*c*), taking into account the current
275 LUC modeling landscape in DGVMs (as briefly reviewed in the Introduction) and the availability of land-
276 use change reconstructions (e.g., Hurtt et al., 2011). The present developments are intended for the case
277 where changes in vegetation coverage are only driven by historical LUC activities and so there is no need
278 to use the dynamic vegetation module of ORCHIDEE. This is different from the LUC implementation in
279 JSBACH DGVM in Reick et al. (2013) where a lot efforts have been devoted to reconciling the
280 vegetation types in the forcing data (primary and secondary natural lands in the Land Use Harmonized
281 data set version 1 or LUH1 data) and the vegetation distributions simulated by the dynamic vegetation
282 module of JSBACH. We focus on including sub-grid land cohorts in the model and implementing a set of
283 hierarchical rules on which land cohorts are subjected to different LUC processes (Table 2). The
284 allocation of natural lands into forest versus grasslands in the model, and the reconciliation of LUH1 land
285 cover distribution and model PFT map, instead, are handled by independent preparations of reconstructed
286 historical land cover map time series.

287
288 In order to compare the simulation results from the gross LUC module with the original net-transition-
289 only LUC module, we separate the gross LUC areas into two additive terms: ‘net change’ equivalent to
290 the original net transition (prescribed by the matrix M_{net}), and ‘land turnover’ for the bi-directional equal
291 land fluxes between any pair of land cover types (prescribed by the matrix M_{turnover}). Similarly, the forest
292 harvest information is prescribed in a third matrix M_{harvest} . For the moment, information for all the three
293 LUC types is provided as fraction of grid cell area. This is a deliberate choice, mainly for the convenience
294 of progressive stage-wise model development. We will come back to the influence of this choice within
295 the land use decision contexts in the Discussion section.

296
297 The key processes of the gross LUC module with CFTs are shown in Fig. 4, comprising in total 6 steps.
298 The LUC module is called at the first day of each year. Input data are the three matrices. M_{net} and M_{turnover}
299 are both square matrices with a size of 4 by 4:

$$\mathbf{M}_{\text{net}} (\mathbf{M}_{\text{turnover}}) = \begin{matrix} & & \begin{matrix} \text{forest} & \text{grassland} & \text{pasture} & \text{cropland} \end{matrix} \\ \begin{matrix} \text{forest} \\ \text{grassland} \\ \text{pasture} \\ \text{cropland} \end{matrix} & \begin{bmatrix} F_{f \triangleright f} & F_{f \triangleright g} & F_{f \triangleright p} & F_{f \triangleright c} \\ F_{g \triangleright f} & F_{g \triangleright g} & F_{g \triangleright p} & F_{g \triangleright c} \\ F_{p \triangleright f} & F_{p \triangleright g} & F_{p \triangleright p} & F_{p \triangleright c} \\ F_{c \triangleright f} & F_{c \triangleright g} & F_{c \triangleright p} & F_{c \triangleright c} \end{bmatrix} \end{matrix}$$

Eq (1)

300

301 Where the element $F_{i \triangleright j}$ denotes the land flux from land cover type i to j , with i, j being elements of the
302 vector of $[f g p c]^T$. The diagonal elements correspond to land fractions intact from any land use
303 transitions and are simply ignored in the LUC module. By definition, M_{turnover} is a symmetric square
304 matrix. M_{harvest} is a matrix with only two elements: harvest area from primary and secondary forests.

305

306 As explained in Sect. 2.1.3, the construction of CFTs within the model follows the “model
307 parameterization hierarchy” shown in Fig. 3a. The cohort age subjected to LUC is one of the most
308 important considerations in land use change decisions, especially in the context of land turnover and
309 forest harvest. This necessitates a re-organization of the CFTs to derive the “LUC hierarchy” shown in
310 Fig. 3b, where Tier 2 information is about areas of different cohorts of the same land cover type, and Tier
311 3 remains on the level of CFTs. So the Step 1 in the LUC module (Fig. 4) is to construct the “LUC
312 hierarchy”, i.e., to calculate within the model the areas of each cohort for each vegetation type.

313

314 When implementing LUC matrices, all information of land transitions between the four basic land cover
315 types must first be downscaled on the cohort tier (i.e., decision on which cohort is subjected to LUC) and
316 then on the CFT tier (i.e., how LUC-affected area is distributed among different comprising meta-classes
317 within each cohort, refer also to Fig. 3b). This is achieved in Step 2 as shown in Fig. 4. Because all the
318 newly established lands, regardless of their originating LUC process, must belong to the youngest CFT of
319 the MTCs that comprise the target land cover type, the ultimate outcome of Step 2 is a single (large)
320 matrix $\mathbf{M}_{\text{nCFT, nMTC}}$ ($\text{nCFT} = \#$ of CFTs, $\text{nMTC} = \#$ of MTCs), which indicates the area transferred from
321 each CFT to the youngest cohort of the concerning MTC. The rules to convert LUC matrices into
322 components of $\mathbf{M}_{\text{nCFT, nMTC}}$ depend on LUC types and will be explained in detail later. But as long as Step
323 2 is done, the remaining steps are rather straightforward.

324

325 Step 3 handles forest wood collection (here ‘collection’ rather than ‘harvest’ is used, to avoid the
326 confusion with forest wood harvest which is a means of forest management), from forest being converted
327 to other land cover types, and forestry harvest (forest remaining forest). We assume that a certain fraction

328 of aboveground woody biomass (i.e., sapwood and heartwood) is lost as instant CO₂ flux into the
 329 atmosphere (i.e., due to on-site disturbance), and that the remaining wood is collected as wood product
 330 pools. Step 4 involves the proper displacement of associated carbon stocks and fluxes from the donating
 331 CFTs to the newly established (youngest) cohorts of MTCs, after wood collection. Notably, the legacy
 332 carbon stocks in litter and soil collected from the donating CFTs are transferred to the newly established
 333 youngest CFTs. Then in Step 5, each youngest CFT cohort is established and initialized, with its fraction
 334 of grid-cell area being the sum of contributing areas given by each source CFT. Finally, in Step 6, a newly
 335 established cohort is merged with the existing youngest CFT cohort if there is one. When merging stocks
 336 or fluxes between the newly established and existing CFTs, an area-weighted mean approach is followed:

$$337 \quad x_{merged} = \frac{x_{new} \times area_{new} + x_{existing} \times area_{existing}}{area_{new} + area_{existing}} \quad \text{Eq (2)}$$

338 Where x is the variable in question (e.g., leaf biomass, soil carbon stock etc.), x_{new} and $x_{existing}$ are the
 339 values of the newly established patch and the existing patch before merging, respectively, and x_{merged} is
 340 the value of the composite patch after merging. $area_{new}$ and $area_{existing}$ are patch areas of the newly
 341 established and the existing patch, respectively.

342
 343 We now return to Step 2, explaining the different rules used to build the $\mathbf{M}_{n\text{CFT}, n\text{MTC}}$ components for
 344 different LUC types. We start with $\mathbf{M}_{\text{harvest}}$ by assuming that it precedes conversion of forest to other land
 345 cover types (i.e., land turnover or net land use change). As is explained, the LUC module is designed to
 346 receive externally prescribed harvest information, especially from the widely used LUH1 reconstruction
 347 (Hurt et al., 2011), rather than to determine harvest volume internally within in the model. The LUH1
 348 distinguishes between harvests from primary and secondary forests and non-forest vegetation but in
 349 ORCHIDEE only harvest from forests is considered. The harvest information is provided as both forest
 350 area and harvested biomass in LUH1. Here we used the area information (a deliberate choice that will be
 351 discussed in Sect. 4). Because of this, ensuring the consistency between the harvest area in the forcing and
 352 that being actually realized in the model is an important consideration. Moreover, as we want to compare
 353 simulated LUC impacts between the two model configurations with and without sub-grid cohorts, it is
 354 necessary to ensure that exactly the same LUC area is realized in both configurations. This involves a set
 355 of decision rules to properly allocate the prescribed harvest area into different forest cohorts (Table 2).

356
 357 Implementation of primary forest harvest is straightforward: we always start with the oldest cohort and
 358 move sequentially downwards to younger ones if older cohorts are exhausted, until the prescribed harvest
 359 demand is fulfilled (Table 2). For secondary forest harvest, we start with intermediate-aged cohorts. But if
 360 the existing area of intermediate-aged cohorts is not sufficient to fulfill the prescribed harvest area, we are

361 left with two options to either search upwards for older cohorts or downwards for younger ones. We
362 decide to first go for upward searching and then for downward searching, if all cohorts older than the
363 intermediate age still cannot fulfill the prescribed harvest demand (Table 2). This rule allows potential
364 temporal changes in harvested area to be accommodated, as explained in Fig. 5. Under such a scheme, (1)
365 at the very beginning (after spin-up) and before the existence of any secondary forests, harvest will start
366 with the oldest cohort, i.e., corresponding to harvest of primary forests (sometimes, because of the
367 inconsistency between the input harvest information and existing forest cohort structure in the model,
368 “secondary” forest harvest could be prescribed for pixels where only primary forests exist in the model).
369 (2) If harvest area of secondary forests remains stable, then as soon as sufficient intermediate-aged
370 cohorts are created via conversion of primary forest to re-growing younger cohorts, a corresponding
371 stable rotation cycle would be maintained in the model as well. (3) If the harvest area increases, the
372 upward searching would allow additional harvest of primary forests (i.e., area subject to the stable
373 rotation is expanded). (4) If the harvest area decreases, the moving of cohorts from younger to older ones
374 independent of any LUC activities would allow restoring older cohorts — e.g. a consequence of
375 abandonment of forest management. (5) Finally, the downward searching for younger cohorts after
376 exhausting all other older cohorts is solely to ensure the consistency between prescribed input harvest
377 area and that actually realized in the model. Hence, this scheme is designed in order to faithfully
378 implement the prescribed harvest areas in the model with an explicit consideration of forest successional
379 states (i.e., primary or secondary). But when this is not possible because of inevitable mismatch between
380 the model and forcing data, harvest areas of primary and secondary forests could mutually compensate for
381 each other in the model, to ensure that their prescribed total harvest area remains realized.

382

383 A number of studies reported that fallow lengths for shifting cultivation could range from a few years to
384 more than 50 years depending on different regions, with the majority being 10–40 years (Bruun et al.,
385 2006; Mertz et al., 2008; Thrupp et al., 1997; van Vliet et al., 2012), and there is a tendency in reduction
386 of fallow lengths possibly because of increased population pressure (van Vliet et al., 2012). Hurtt et al.
387 (2011) assumed a mean residence time of 15 years for shifting cultivation for tropical regions in the
388 LUH1 reconstruction data. Based on these reports, we assume forest clearance for shifting cultivation to
389 occur primarily in secondary forests, and treat it similarly as secondary forest harvest when allocating the
390 prescribed LUC area into different cohorts (Table 2). The only difference is that the destination land
391 cover remains forest in the case of forest harvest but is agricultural land in the case of shifting cultivation.
392 For all other land transfers in shifting cultivation (e.g., pasture to forest), we start exclusively from the
393 oldest cohort and move downwards to younger ones (Table 2). For net land use change, priority is again
394 given to older cohorts followed by younger ones (Table 2).

395

396 Finally, we still need to downscale the LUC area in each cohort to its component CFTs. This is done by
397 allocating the LUC area in each cohort to its member CFTs in proportion to the existing area of each CFT.

398 **2.1.5 LUC processes that remain unchanged in the model**

399 ORCHIDEE simulates two wood product pools with a turnover length of 10 years and 100 years,
400 respectively. Fractions of aboveground woody biomass as instant on-site losses (F_{instant}), and entering into
401 the two wood product pools ($F_{10\text{yr}}$, $F_{100\text{yr}}$) follow the values in the original net-transition-only LUC scheme
402 (Piao et al., 2009a), as shown in Table 3. Other biomass compartments (i.e., leaves, fine roots, coarse
403 roots, fruits and reserve pool) are transferred to litter pools during forest harvest or deforestation. Carbon
404 in the two wood product pools is then released into the atmosphere according to their respective turnover
405 time, and this flux contributes to the overall land carbon balance as a source term (see the next section).

406

407 Other processes relevant to LUC are left unchanged with the original model version. In particular, crop
408 harvest is applied to cropland CFTs with a fraction of 45% of biomass turnover being ‘harvested’ in the
409 model and exported outside the ecosystem (Piao et al., 2009a). Pasture CFTs are also harvested in the
410 same fashion. Agricultural harvest and associated fluxes to the atmosphere through food consumption or
411 livestock feeding are assumed to happen locally in the model during the same year of harvest, without
412 considering spatial relocation through international trade. Fires are simulated with a prognostic module,
413 but as explained in Sect. 2.1.3, fire disturbances do not lead to creation of young cohorts, but only their
414 carbon consequences (e.g., emissions, vegetation mortality, etc.) are included.

415 **2.2 Simulation set-up**

416 **2.2.1 Definition of land-use change emissions (E_{LUC}) and carbon flux sign convention**

417 The land carbon balance simulated by ORCHIDEE-MICT v8.4.2 (i.e., net biome production or NBP),
418 when land use change is included, is defined as:

419

$$420 \text{NBP} = \text{NPP} + F_{\text{Inst}} + F_{\text{Wood}} + F_{\text{HR}} + F_{\text{Fire}} + F_{\text{AH}} + F_{\text{Pasture}} \quad \text{Eq (3)}$$

421

422 Where NPP is the net primary production, and all fluxes with “F” notation are outward carbon fluxes
423 from the land system (they are assigned a negative sign following the ecosystem convention, indicating
424 that carbon is lost from ecosystems), with F_{Inst} for the instantaneous carbon flux during LUC (e.g., carbon
425 release arising from site preparation, land-clearing burning etc.), F_{Wood} for the delayed carbon release due
426 to wood products degradation, F_{HR} for heterotrophic respiration from litter and soil organic carbon
427 decomposition, and F_{AH} for agricultural harvest on both croplands and pastures, and F_{Pasture} for carbon

428 sources from pastures other than harvest, i.e., export of animal production and methane emissions (see
429 Chang et al., 2015 for details). F_{Inst} and F_{Wood} are both fluxes on an annual time scale that depend only on
430 wood mass at the time of forest clearing and the respective wood product degradation rates (see Sect.
431 2.1.5). F_{HR} is simulated at a time step of 30 minutes and depend on soil temperature and moisture. F_{Fire} is
432 simulated with a prognostic fire module SPITFIRE (Yue et al., 2015).

433

434 The LUC emissions (E_{LUC}) are quantified as the difference in simulated NBP between two paired
435 simulations, with LUC (or a specific LUC process) included in one simulation but not the other one:

436

$$437 \quad E_{\text{LUC}} = \text{NBP}_{\text{LUC}} - \text{NBP}_{\text{control}} \quad \text{Eq (4)}$$

438

439 Where, NBP_{LUC} and $\text{NBP}_{\text{control}}$ are NBP simulated with and without LUC. A negative E_{LUC} denotes a
440 carbon source to the atmosphere, i.e., ecosystem carbon sink is reduced because of land use change. This
441 definition follows Pongratz et al. (2014, Page 178) and is also the same as used in TRENDY (Sitch et al.,
442 2015) simulations and the existing global carbon budget analysis (Le Quéré et al., 2016). As explained by
443 Pongratz et al. (2014), such a definition quantifies the “net” LUC flux because it integrates both
444 emissions to the atmosphere (e.g., deforestation) and uptakes by potentially recovering vegetation (e.g.,
445 agricultural abandonment). More specifically, this corresponds to the definition “D3” using uncoupled
446 DGVM simulations in Pongratz et al. (2014, Eq. 15c, Page 187), which contains instantaneous fluxes,
447 legacy fluxes, and “loss of additional sink (source) capacity (LOAS)”.

448

449 Instantaneous fluxes refer to the carbon emissions directly arising from LUC, often occurring within the
450 first year since LUC (F_{Inst} in our case). Legacy fluxes arise from the readjustment of carbon stocks to the
451 new type of vegetation and/or the changes in management intensity over time (Pongratz et al., 2014), and
452 “loss of additional sink (source) capacity (LOAS)” refers to the carbon sink/source difference between the
453 actual land cover after LUC and the otherwise potential one under environmental perturbations. All other
454 flux terms on the right side of Eq. (3) except F_{Inst} contribute to the legacy fluxes and LOAS. Here, as our
455 model development mainly distinguishes the biomass carbon of secondary forests, it’s expected that F_{Inst}
456 and F_{Wood} will be the major fluxes to have influence on simulated E_{LUC} . To facilitate the demonstration of
457 model behaviour, we refer to F_{Inst} and F_{Wood} collectively to as “LUC-associated direct fluxes” and their
458 variations will be examined in detail by using an idealized grid cell simulation.

459

460 The model developments presented here enable us to make two parallel simulations that include LUC:
461 with and without sub-grid age dynamics. Their simulated E_{LUC} can thus be compared, to separate the

462 effect of including sub-grid age dynamics. Henceforth for briefness, we denote the simulation without
463 sub-grid age dynamics as S_{ageless} , and the one with age dynamics as S_{age} .

464 **2.2.2 Idealized simulation on a single grid cell**

465 We conducted an idealized grid cell simulation with prescribed land cover and LUC matrices, to compare
466 in detail the simulated carbon pools and fluxes between S_{age} and S_{ageless} . The geographical coordinates of
467 the simulation site are 9.25°S, 18.25°E at a 0.5° global grid, in the north of Angola, Africa, where the
468 miombo woodlands are known to be subject to practices of shifting cultivation. The ESA CCI land cover
469 map for the 5-year period of 2003–2007 (<https://www.esa-landcover-cci.org/>) shows a dominant fraction
470 of tropical deciduous broadleaf forest for this grid cell. Hence for the idealized experiment, the initial
471 vegetation composition is prescribed as 85% of tropical deciduous broadleaf forests and 15% of C4
472 croplands. As we will focus on the LUC impacts, other model forcings (climate, atmospheric CO₂, etc.)
473 are held constant, with climate input data recycling the year of 1901 (CRUNCEP-v5.3.2 climate data,
474 <https://esgf.extra.cea.fr/thredds/fileServer/store/p529viov/cruncep/readme.html>) and atmospheric CO₂
475 concentration being fixed at 350 ppm. The model is tested for a hypothetical scenario of constant annual
476 land turnover with 5% of grid cell area between forest and C4 cropland. Forest harvest of the same annual
477 areal fraction is expected to have largely similar impact. The spin-up was run for 450 years until biomass
478 and soil C stocks reached equilibrium and the mean annual net biome production (NBP) was close to zero
479 without including any LUC. Starting from the spin-up, a transient simulation with the prescribed LUC
480 matrix was performed for 100 years.

481 **2.2.3 Simulation over Southern Africa**

482 Subsequently, the model behaviour has been documented for a real-world case over the region of
483 Southern Africa (south to the equator of the African continent). All three LUC types occurred historically
484 in this region, making it ideal to demonstrate model behaviour regarding forest cohort dynamics as
485 presented in Fig. 5. This regional simulation serves a single purpose — to further exemplify model
486 features that cannot be sufficiently demonstrated over a grid cell.

487
488 The regional simulation is done at 2° resolution for 1501–2005. We used the land use reconstruction from
489 LUH1 covering 1501–2013 (Hurt et al., 2011, http://luh.umd.edu/data.shtml#LUH1_Data) re-gridded
490 from the original 0.5° to a 2° spatial resolution. We derived from the LUH1 dataset the matrices of the
491 three types of land use change: net land use change, land turnover and wood harvest. Land turnover
492 information is extracted from LUH1 as the minimum land fluxes between two vegetation types. Wood
493 harvest from primary and secondary forests in LUH1 is used, while wood harvest from non-forest is not.
494 Climate forcing data are from CRUNCEP-v5.3.2 at a 2° resolution. For the spin-up, climate data were

495 cycled from 1901 to 1910, with atmospheric CO₂ concentration fixed at 1750 level (277 ppm). In the
496 transient simulation, atmospheric CO₂ concentration began to increase in 1750, climate data were varied
497 starting 1901. The dynamic vegetation module was turned off, in order to apply the prescribed historical
498 land use change. Factorial simulations are conducted to highlight changes in areas of different forest
499 cohorts when different LUC processes are included, as shown in Table 4.

500
501 Each forest MTC has six CFTs to represent six cohorts. The woody mass thresholds are set in a way that
502 they correspond roughly to the woody masses at ages of 3, 9, 15, 30, 50 years, and the mature or primary
503 forest (with an age greater than 50 years) during the spin-up simulation, respectively, for Cohort₁ to
504 Cohort₆. The Cohort₃ with an age of 15 years is the primary target for secondary forest harvest and land
505 turnover (or shifting cultivation), corresponding to the mean residence time of 15 years of shifting
506 cultivation assumed in LUH1 data (Hurtt et al., 2011). We set two CFTs for each herbaceous MTC with a
507 high and low soil carbon density, respectively. The CFT thresholds of soil carbon stock are the same for
508 all herbaceous MTCs. We first calculate the maximum soil carbon stock of all MTCs (including the forest
509 ones) at the end of spin-up for each grid cell, and cohort thresholds are then taken as this maximum value
510 and its 65% value. Because the energy balance in ORCHIDEE-MICT is resolved for the average of all
511 CFTs over a grid cell, and the hydrological balance is resolved for three sub-grid water columns (i.e. the
512 water column of bare soil, forest and herbaceous vegetation), we expect the factors influencing soil
513 carbon decomposition (e.g., soil temperature, soil moisture) to have little variation among CFTs of the
514 same MTC. This justifies the small number of herbaceous CFTs, for the sake of computation efficiency.
515 Overall, this feature of separating herbaceous MTCs into multiple cohorts is coded more as a “place
516 holder” for the current stage of model development rather than having solid scientific significance. Fully
517 tracking soil carbon stocks of different vegetation types and their transient changes following land use
518 change, would require a much larger number of cohorts than used in this study.

519 **3 Results**

520 **3.1 Grid cell simulations with and without sub-grid forest age dynamics**

521 **3.1.1 Temporal patterns of biomass carbon stock during the spin-up and transient simulations**

522 Figure 6a and 6b exhibit the evolution of above- and belowground biomass for both S_{ageless} and S_{age}
523 simulations, for the spin-up and transient simulation for a test grid cell located in Angola. The results for
524 the S_{age} simulation are shown for individual cohorts (Cohort₁ to Cohort₆). For this test an annual forest-
525 cropland turnover of 5% of the grid cell area was imposed. Figures 6c-h present changes in the ground
526 fractional cover of different forest cohorts during the transient simulation. S_{ageless} and S_{age} share the same
527 biomass accretion with time during the spin-up, but S_{age} shows a succession of forest cohorts — with

528 biomass moving from one cohort to the next (Fig. 6a & 6b). At the end of the spin-up, all biomass is
529 found in Cohort₆ (i.e., the oldest cohort), with an initial forest cover of 85%.

530

531 More differences emerge when entering the transient simulation. Aboveground biomass in S_{ageless} shows
532 an initial sharp drop followed by a more gradual decline under constant land turnover, because biomass of
533 the single forest patch is constantly ‘diluted’ by merging with the new forest patch with a low biomass,
534 which is established as a result of land turnover (see also Fig. 1). Belowground biomass, however, shows
535 a corresponding initial drop but then slightly increases. Eventually, both above- and belowground
536 biomass stocks in S_{ageless} reach a new equilibrium, which are lower than their values at the end of the spin-
537 up. By contrast, in S_{age} , the fraction of Cohort₆ declines with the start of the transient simulation because
538 of conversion to cropland. This decline continues until the 12th year, after which the remaining Cohort₆
539 covers only 30% of the grid cell (Fig. 6h). Younger cohorts are progressively created as forests restore
540 after shifting agriculture abandonment, with the Cohort₁ (i.e., the youngest one) appearing during the
541 initial 6 years after the start of LUC, after which its biomass is moved into Cohort₂ (Fig. 6c & 6d).
542 Cohort₃ starts to appear at the 12th year when biomass in Cohort₂ moves into it. Then its coverage declines
543 as this cohort, rather than Cohort₆, is used as the source for shifting cropland, according to the model rule
544 that secondary forest is taken prior to primary forest in the land turnover (Fig. 5). After the initial 15 years
545 (the rough age of Cohort₃), the fractions of Cohort₁, Cohort₂ and Cohort₃ reach a dynamic stable state. As
546 Cohort₃ is being constantly converted to cropland, it has never developed into Cohort₄ or Cohort₅. This
547 explains the zero fractions of these two latter cohorts in Fig. 6f & 6g.

548

549 While the aboveground biomass continuously grows during the spin-up, the belowground biomass first
550 increases with time and then slightly declines before reaching the equilibrium value. This is because
551 ORCHIDEE-MICT has a preferential allocation of NPP to belowground sapwood when forests are
552 young. The small decline in belowground biomass in the late spin-up stage thus results from an almost
553 stabilized NPP (under a big-leaf approximation), a reduced belowground allocation and a constant
554 mortality. Because of this feature, ORCHIDEE-MICT creates a higher belowground biomass in younger
555 forest cohorts (e.g., Cohort₂ and Cohort₃ in Fig. 6a & 6b) in S_{age} than the single forest patch in S_{ageless} in
556 the transient simulation. However, the aboveground biomass in younger Cohort₂ and Cohort₃ in S_{age} is
557 lower than S_{ageless} . The difference in biomass influences the simulated E_{LUC} between these two
558 simulations, as we will discuss in detail later.

559 3.1.2 LUC-associated direct carbon fluxes

560 As shown in Fig. 7a, in S_{ageless} , the instantaneous carbon flux resulting from LUC follows the same
561 temporal pattern than the aboveground biomass, as it is simulated as a fixed fraction of aboveground

562 woody mass (sapwood and heartwood) (see Sect. 2.1.5). In S_{age} , for the initial 12 years, the Cohort₆
563 (undisturbed mature forest) is cleared, so that the instantaneous LUC carbon flux is higher than that in
564 $S_{ageless}$ (where the biomass of the single forest patch is reduced immediately when the land turnover
565 starts). After that, the instantaneous flux shows a stark drop in S_{age} when the Cohort₃ enters the land
566 turnover. Since then until the end of the simulation, S_{age} has kept a constantly lower instantaneous flux
567 than $S_{ageless}$ because the LUC-perturbed equilibrium biomass is higher in the latter case (Fig. 6a). As a
568 fixed 10% of aboveground woody biomass enters the wood product pool with a 10-year turnover time,
569 delayed carbon emissions from wood products degradation in both simulations are smaller than the
570 instantaneous LUC carbon fluxes. They peak around the 12th year after LUC and remain stable afterwards
571 (Fig. 7a). Overall, S_{age} has a higher LUC-associated direct carbon flux than $S_{ageless}$ for the first 12 years,
572 and a lower one afterwards (Fig. 7a). The cross point for the cumulative LUC-associated direct fluxes
573 equal in S_{age} and $S_{ageless}$ is around the 20th year (Fig. 7b). When summing over the whole simulation period
574 (100 years), the cumulative fluxes by $S_{ageless}$ is lower in S_{age} by about 11 kg C m⁻², or ~110 g C m⁻² yr⁻¹
575 (Fig. 7b) than $S_{ageless}$.

576 3.1.3 LUC emission and its disaggregation into underlying component carbon fluxes

577 As defined in Eq (4), the net LUC carbon emission (E_{LUC}) is diagnosed as the difference in NBP between
578 the LUC simulation and the control one. Since NBP is further a composite flux determined by carbon
579 uptake and releases (Eq. 3), the difference in $E_{LUC\ age}$ and $E_{LUC\ ageless}$ can be disaggregated into the effect of
580 each underlying flux, which differs between the LUC simulation and the control simulation. Figure 8
581 presents such disaggregation. All positive values indicate an enhanced carbon uptake or diminished
582 release in the LUC simulation compared to the control one, whereas negative values indicate the reverse
583 cases (i.e., negative values indicate a contribution to enhance E_{LUC}).

584

585 First of all, $S_{ageless}$ (no age dynamics) simulates a larger magnitude (i.e., a larger absolute E_{LUC} value) of
586 mean annual E_{LUC} than S_{age} (with age dynamics), by about 26 g C m⁻² yr⁻¹. Second, for both simulations,
587 the simulated E_{LUC} is an outcome of LUC-associated direct fluxes being compensated for by changes in
588 other fluxes, all of which have an effect to reduce E_{LUC} in this example: NPP, heterotrophic respiration,
589 fire carbon emissions and agricultural harvest.

590

591 NPP is higher in LUC simulations than in the control. This is because young forests are established in the
592 former case (either by merging with existing forest patch or not), leading to a younger leaf age than in the
593 control simulation, which is parameterized to have a higher photosynthetic capacity than older leaves in
594 the model. This suggests the model can somewhat integrate the effect of recovering young forests or

595 intermediate-aged forests with a higher productivity than the old-growth forests, as reported by Tang et al.
596 (2014) using observation data.

597

598 Averaged over the LUC simulation period of 100 years, both S_{age} and $S_{ageless}$ show lower heterotrophic
599 respiration (F_{HR}) than the control. This is because the biomass stock is lower in the LUC simulations
600 (despite a higher NPP, biomass turnover is accelerated due to site perturbation and wood collection in the
601 process of clearing forest for cropland), causing less litter input and less soil carbon stocks (data not
602 shown). The S_{age} simulation shows a much smaller reduction in F_{HR} , mainly because a higher
603 belowground litter is maintained, which results from a high belowground litter input out of land turnover,
604 driven by a high belowground biomass, as explained in Sect. 3.1.1 (Fig. 6a).

605

606 Decreases in fire carbon emissions (F_{Fire} , from prognostically simulated ‘natural fires’ but not ‘land-
607 clearing fires’) in the LUC simulations in contrast with the control are because the aboveground litter
608 (dominant fuel for fires) is reduced by land turnover. Reductions in fire emissions, and reductions in
609 heterotrophic respiration, are thus driven by the same process, i.e., a reduction in aboveground standing
610 biomass. LUC simulations also result in lower agriculture harvest (F_{AH} , from cropland) although there is
611 no change in the cropland area; this is due to lower biomass in young crop, as the crop harvest is assumed
612 as a constant fraction of the biomass turnover (i.e., routine mortality) at a daily time step. The lower crop
613 biomass in the LUC simulations here is because crop saplings are established on the first day of each
614 calendar year, right before the seasonal biomass peak for the southern hemisphere, which artificially
615 reduces the standing biomass.

616

617 Overall, the lower E_{LUC} magnitude in S_{age} is a result of the lower LUC-associated direct fluxes having
618 been partly compensated for by a higher heterotrophic respiration. The relative magnitudes between E_{LUC}
619 $_{age}$ and $E_{LUC}_{ageless}$ are dominated by these two fluxes, while other fluxes play a less important role.

620 **3.2 Forest cohort area changes as a result of historical land use change over Southern Africa**

621 One of the useful features of our model development is to account for sub-grid forest age dynamics as a
622 result of historical land use change, as illustrated in Fig. 9 for Southern Africa. When no land use change
623 is included (S_0 , the control simulation shown in light blue), the areas of all forest cohorts are constant
624 over time. Except that younger cohorts have a very small area ($<0.1 \text{ Mkm}^2$) (Cohort₂ and Cohort₃,
625 probably due to improper cohort thresholds on a very small number of grid cells), almost all forests are
626 found in Cohort₆, which resembles mature forests. In S_1 where only net land use change is considered, the
627 area of Cohort₆ decreases consistently over time due to conversion of forest to other land cover types (Fig.
628 9a). Occasional increases in areas of other younger cohorts are also present, corresponding to the periods

629 when forest gain happens due to net land use change, for instance, afforestation or reforestation around
630 1700s and in the latter half of the 20th century (Fig. 9a). This is consistent with our rule that forest from
631 abandonment of agriculture is established in the youngest cohort (Fig. 5b – on the right), and progressive
632 movement of forests from younger to older cohorts are also visible as the small waves in the curves of
633 Fig. 9b–f.

634

635 In the S2 simulation with both net land use change and land turnover, large areas of younger forests, in
636 particular of Cohort₁ and Cohort₂, begin to appear as a result of continual creation of forests from land
637 turnover, and subsequent moving of forests from Cohort₁ to Cohort₂. Their temporal changes over time
638 follow those of the forest area subject to land turnover, as shown in Fig. 9a (green dashed line). The area
639 of Cohort₃, however, does not see as much increase as in the two younger cohorts, because forests of
640 Cohort₃ are the primary target for clearance in land turnover and thus are incessantly converted back to
641 (shifting) agriculture. As a result, about half of mature forests (Cohort₆) are left intact from LUC by 2005
642 (Fig. 9h). Most interestingly, when there is a decline in the turnover-impacted area around 1700s (the
643 green arrow in Fig. 9a), a corresponding decline in the area of Cohort₁ is found because these forests
644 move into the next cohort. This pattern of decrease in the current cohort accompanied by the according
645 increase in the next one then propagates into other older cohorts with time, which results in a delayed
646 increase in Cohort₅ around 1750s (Fig. 9g), and finally in Cohort₆ as well (but less prominent because of
647 its already large area). This demonstrates the model feature of older forest recovery in case of decreased
648 land turnover or wood harvest, as explained in Fig. 5b (right hand side). Last, when we further include
649 forest harvest in S3 simulation, because wood harvest area only started to rise in the middle of 20th
650 century, larger areas of Cohort₁ and Cohort₂ cohorts are found compared with S2 in the latter half of the
651 last century, and forest area in Cohort₆ is accordingly lower, being converted to younger cohorts as a
652 result of harvest.

653 **4 Discussion**

654 DGVMs, either used in an off-line mode or coupled with climate models, are powerful tools to investigate
655 the role of past and future land use change in the global carbon cycle perturbed by human activities
656 (Arneth et al., 2017; Le Quéré et al., 2016). Therefore, a more realistic representation of LUC processes
657 in these models is a scientific priority. We included two new features in ORCHIDEE-MICT v8.4.2: gross
658 land use change and forest wood harvest, and sub-grid vegetation cohorts. In a recent review (Prestele et
659 al., 2016), proper representation of gross land use change or sub-grid bi-directional land turnover has been
660 identified as one of the three major challenges in implementing LUC in DGVMs for credible climate
661 assessments, despite that these have already been pioneered by some models (Table 1). Large

662 underestimation of LUC emissions would occur when gross land use change is ignored, as is shown by
663 several model results being reviewed in Arneth et al. (2017).

664

665 Shifting cultivation, or forest wood harvest, or more in general forest management, often involves a stable
666 fallow length or rotation cycle, which involves secondary forests rather than primary ones. In tropical
667 regions, fallow lengths in shifting cultivation range from 10 to 40 years (Bruun et al., 2006; Mertz et al.,
668 2008; Thrupp et al., 1997; van Vliet et al., 2012), with a tendency of reduction in fallow length. In Latin
669 American tropics, agricultural abandonment have already led to prominent growth of secondary forests
670 (Chazdon et al., 2016; Poorter et al., 2016). Forest management, including wood harvest, is more
671 common in temperate and boreal regions. In European forests, rotation lengths depend on tree species,
672 regional climate and management purposes, ranging from 8–20 years in coppicing systems in southern
673 Europe to 80–120 years in northern countries (McGrath et al., 2015). The prevalence of secondary forests
674 associated with land use and land use change therefore calls for their representation in DGVMs,
675 especially when modeling land use change.

676

677 To our knowledge, Shevliakova et al. (2009) has been the first study to include both sub-grid secondary
678 lands and gross transitions in the LM3V model, but the number of PFTs and secondary land tiles are
679 limited in their study (up to in total 12 secondary land tiles compared with 50 in our study). Stocker et al.
680 (2014) included secondary land in LPX-Bern 1.0 but only one tile of secondary land is available. Yang et
681 al. (2010) examined the contribution of secondary forests to terrestrial carbon uptake using the ISAM
682 model by explicitly including secondary forest PFTs, but they did not include the dynamic clearing of
683 secondary forests in land use change, nor shifting cultivation. Therefore, none of these studies have
684 included a dynamic decision rule regarding the ages of cohorts to be targeted in different LUC processes
685 or the possibility to target different cohort ages in different geographical regions. ORCHIDEE-CAN is
686 especially designed to address forest management and species change. Although certain land use change
687 such as wood harvest and net land cover changes are included, a more comprehensive LUC scheme
688 addressing gross change is missing (Naudts et al., 2015).

689

690 The gross land use change combined with sub-grid cohorts presented here has shown some promising
691 results. We first confirmed that including gross land use change leads to additional carbon emissions.
692 However, these additional emissions tend to be overestimated when secondary forests are not explicitly
693 accounted for. The idealized grid cell simulation well explained the mechanism driving such
694 overestimation in S_{ageless} simulations. The results presented here are closely linked with our model
695 parameterization and in particular, the decision rules regarding which forest cohorts to apply for specific

696 LUC processes (Table 2). Land turnover and secondary forest harvest are parameterized to target
697 intermediate-aged cohorts as a priority. This is the core mechanism driving the lower LUC emissions
698 when sub-grid forest age structure is accounted for.

699
700 As a preliminary effort to demonstrate the model behaviour, the land turnover parameterization is heavily
701 tied with the input LUC forcing data (LUH1), so that the age of Cohort₃ (as the primary target for land
702 turnover) is set as ~15 years, following the assumed mean residence time of shifting cultivation in LUH1
703 data set (Hurtt et al., 2011). The model simulations showed that this parameterization is crucial, because it
704 largely determines the rotation length in the model, and consequently, the amount of carbon stocks
705 subjected to LUC and the difference in estimated LUC emissions between the two model configurations
706 (S_{age} and $S_{ageless}$). In this regard it should be noted that the information on rotational lengths of shifting
707 cultivation or forest harvest is spatially unbalanced and that at present no systematic global compilation
708 exists. The universal setting used in this study is due to the absence of such a compilation. In fact,
709 because the thresholds in woody mass to distinguish forest cohorts could be configured via a spatial map
710 in the model and such maps could vary among different years, and because the primary cohort target is
711 not hard-coded and can be parameterized as well, it is rather straightforward to apply temporally and
712 spatially different rotation lengths in the model. Such a feature is well considered in the model
713 development design and could be tested when information on spatially and temporally explicit forest
714 rotation lengths or associated biomass thresholds is available.

715
716 In the following paragraphs we will discuss the decisions that were marked as “deliberate” and their
717 potential impacts on modeled LUC stocks and fluxes. First, the LUC module developed is intended for
718 usage within DGVMs, and forced with external data sets that provide information on land flows between
719 different land cover types. It is not intended to supersede a land use change model per se, which simulates
720 land use change using other available social and economic information such as population, food demand,
721 wood demand, etc. (Hurtt et al., 2011). In this sense, the LUC module implementation has to inevitably
722 take into account the details of information in forcing data that are available, and to reconcile the potential
723 mismatch between the model and forcing data. For example, the LUC module presented here can
724 accommodate forest wood harvest from primary and secondary forests when these two sources are
725 distinguished in the forcing data, but hierarchical decision rules are also made when the model and
726 forcing data disagrees (e.g., Fig. 5), such as that prescribed “secondary forest wood harvest” can actually
727 harvest a “primary forest” in the model if all younger cohorts are exhausted.

728

729 Second, because of this clearly defined border of the LUC module to use land areas as the input
730 information, model output from ORCHIDEE-MICT can potentially disagree with the socio-economic
731 information used to generate the LUC forcing data. For instance, crop yield simulated by ORCHIDEE
732 may differ with that used to convert food demand/consumption to cropland area, so that simulated crop
733 output or food production may disagree with historical food demand in the real world. The same applies
734 on forestry wood production: simulated harvest wood volume might disagree with the wood volume
735 actually used to generate the harvest area information — the harvested wood biomass information is
736 provided in LUH1 data set but not used as an input in the current stage of model development. This
737 largely raises the issue that, to what extent the information that drives land use change decisions can be
738 *internally* integrated into DGVMs, for example, to use directly crop production, rather than cropland area,
739 or wood volume, rather than forest harvest area as the model input. One potential obstacle is that
740 statistical information (e.g., on wood volume demand) is often available on regional basis (FAO global
741 forest resource assessment, <http://www.fao.org/forest-resources-assessment/en/>; eurostat,
742 <http://ec.europa.eu/eurostat/data/database>), and complex decision rules are needed to disintegrate such
743 information on spatial grids that DGVMs are operated on. But in general and over a long term, land use or
744 land management decisions need to be integrated directly into DGVMs. ORCHIDEE-CAN has integrated
745 forest management decisions based on simulated tree diameters and stand density, so that harvested wood
746 biomass is actually a model output that can be validated against historical statistical data (Naudts et al.,
747 2016).

748

749 The developments presented here mainly build on a model structure that distinguishes differently aged
750 cohorts. Nonetheless, we have built a better tool to address the impacts of historical land use change on
751 carbon cycle and climate with these developments. Forest demographics, which are shown to have great
752 impact on the current northern hemisphere carbon sink (Pan et al., 2011; Piao et al., 2009b), either as a
753 result of active afforestation, or agricultural abandonment or natural regeneration, could then be explicitly
754 investigated. These developments also make it possible to verify modeled global and regional forest age
755 distribution using independent age information from either forest inventory or remote sensing. The model
756 version used here has incorporated the developments in pasture and cropland modules (Chang et al.,
757 2015; Wang et al., 2017). On a regional scale such as Europe, where the comprehensive forcing data are
758 available, it is possible to go beyond the carbon emissions only by LUC activities, but also to include
759 LUC-induced changes in emissions of other greenhouse gases such as methane and nitrogen oxide.

760 **5 Conclusions**

761 We have presented new developments made in a global vegetation model, to include gross land use
762 change and forest wood harvest, in combination with explicit representation of sub-grid forest age
763 dynamics. Furthermore, a set of decision rules regarding the land cohorts to be targeted in different LUC
764 processes have been implemented. The presented simulation results are specific of the ORCHIDEE-
765 MICT model, but the methods are generic for other DGVMs. We demonstrated through an idealized pixel
766 simulation that gross land use change leads to additional emissions but accounting for sub-grid land
767 cohorts yields lower emissions than not. Over the region of Southern Africa, the model is able to account
768 for changes in different forest cohort areas along with the temporal changes in different LUC processes,
769 including regrowth of old forests when LUC area decreases. Our developments provide the possibility to
770 account for forest demography when evaluating LUC impacts on global carbon cycle and climate.

771 **6 Code availability**

772 The source code for ORCHIDEE-MICT version 8.4.2 is available online
773 ([https://forge.ipsl.jussieu.fr/orchidee/browser/branches/ORCHIDEE-](https://forge.ipsl.jussieu.fr/orchidee/browser/branches/ORCHIDEE-MICT/tags/ORCHIDEE_MICT_GLUC_8.4.2)
774 [MICT/tags/ORCHIDEE_MICT_GLUC_8.4.2](https://forge.ipsl.jussieu.fr/orchidee/browser/branches/ORCHIDEE-MICT/tags/ORCHIDEE_MICT_GLUC_8.4.2).) but its access is restricted to registered users. Requests
775 can be sent to the corresponding author for a username and password for code access. ORCHIDEE-
776 MICT is governed by the CeCILL license under French law and abiding by the rules of distribution of
777 free software. One can use, modify and/or redistribute the software under the terms of the CeCILL license
778 as circulated by CEA, CNRS and INRIA at the following URL: <http://www.cecill.info>.
779

780 **7 Data availability**

781 Primary data and scripts used in the analysis and other supplementary information that may be useful in
782 reproducing the authors' work can be obtained by contacting the corresponding author.
783

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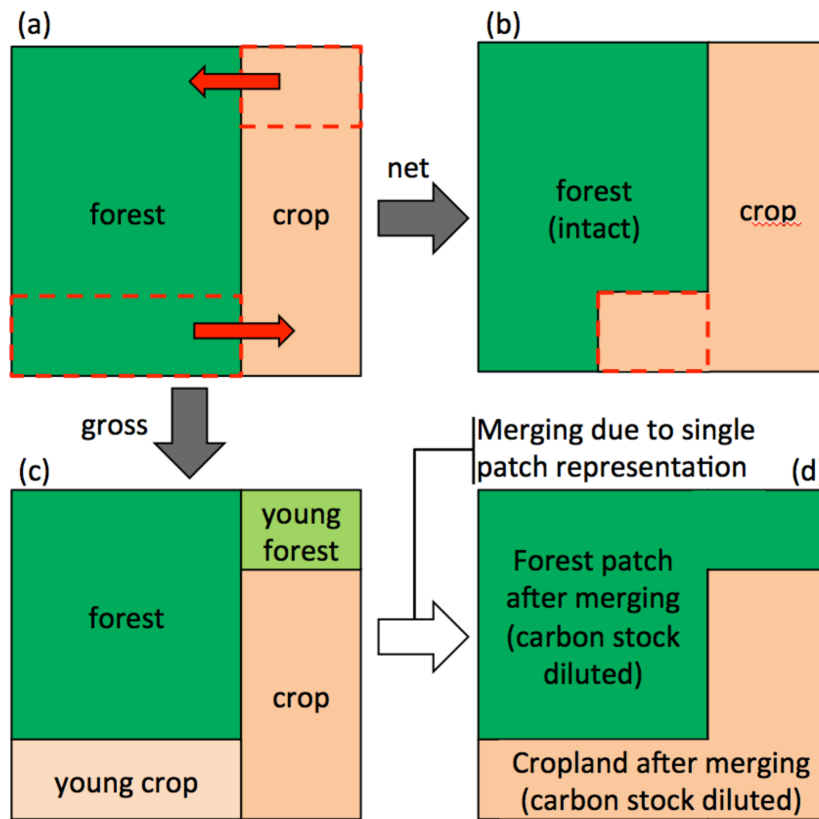
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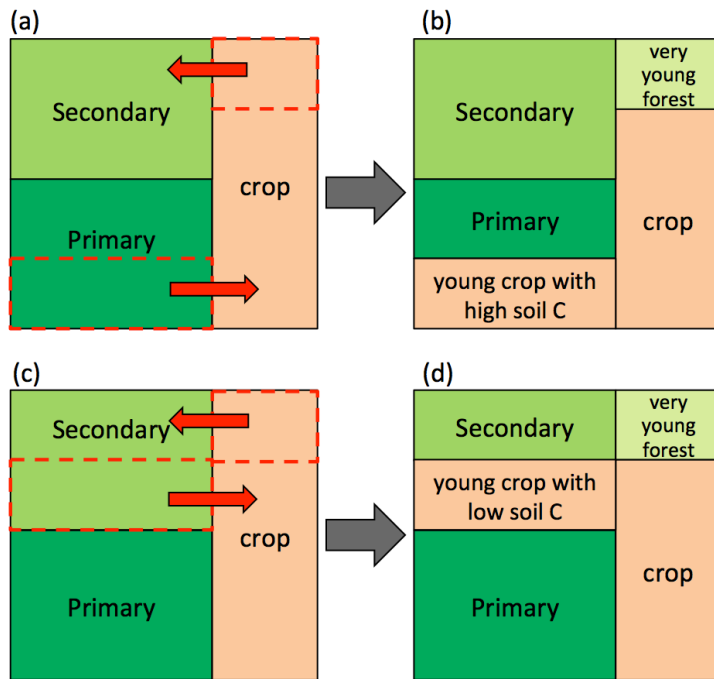
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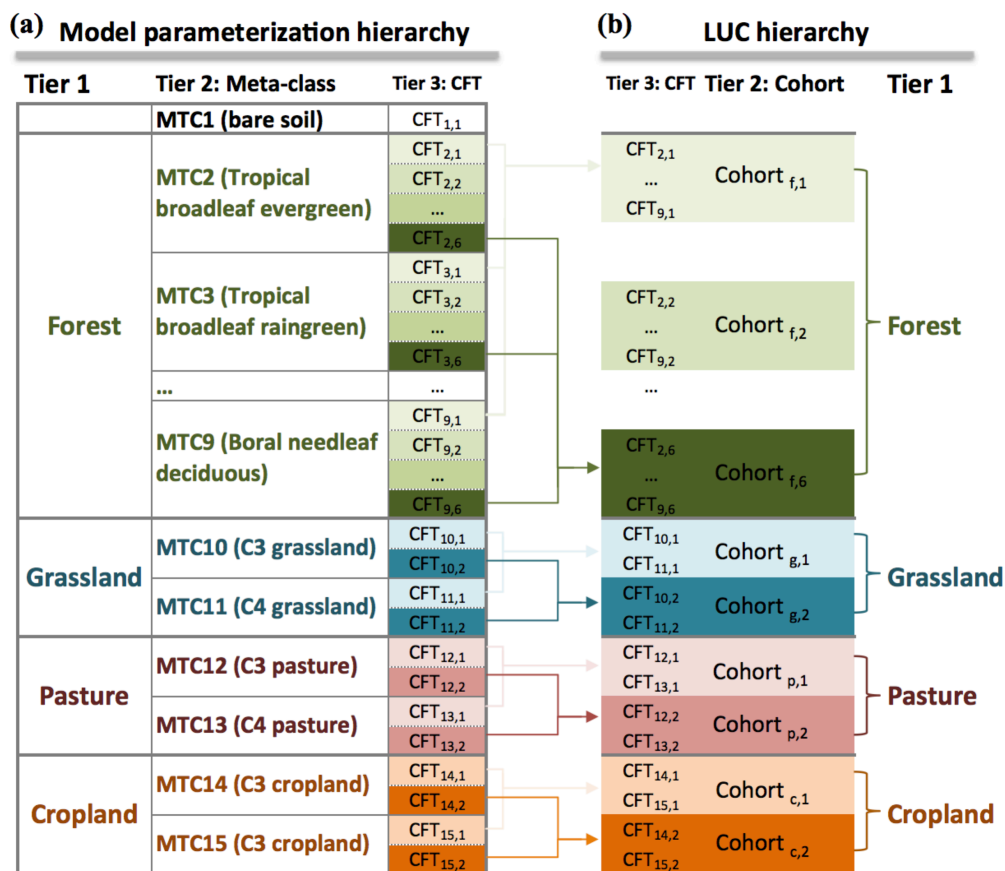


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 992 Fig. 1 Schematic illustration of gross versus net land use change, with each land cover type being
 993 represented using a single patch within a model grid cell. The figure is adapted from Stocker et al. (2014).
 994 (a) Original fractions of forest and cropland before land use transitions. Dashed red rectangles indicate
 995 areas subject to LUC and red arrows indicate land flow direction. Here LUC consists of a net loss in
 996 forest and a simultaneous bi-directional flow between forest and cropland. (b) Post-LUC fractions of
 997 forest and cropland following the original LUC scheme of net transitions only in ORCHIDEE. Bi-
 998 directional land flow is omitted, with only cropland area being expanded to account for its net increase as
 999 a result of the net forest loss, as indicated by the dashed red rectangle. The soil carbon stock of the new
 1000 cropland patch is an area-weighted mean between that of the original cropland, and the legacy stock from
 1001 the former forest. Carbon stock of the remaining forest patch is left intact. (c) Intermediate post-LUC land
 1002 cover pattern after accounting for gross transition. Both the net loss of forest and bi-directional land flows
 1003 are accounted for, with two young patches of forest and cropland being established, respectively. (d) Final
 1004 state of post-LUC land cover after accounting for gross LUC with no sub-grid cohorts. The carbon stocks
 1005 of the remaining (original) forest and the newly created forest are immediately merged following LUC

1006 because there are no sub-grid cohorts. The same applies for cropland as well. Note that although forest
 1007 and cropland fractions are ultimately the same as in (b), the carbon densities are different.
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 1012 Fig. 2 Gross land use change involving forests with different ages under a model scheme capable of
 1013 representing sub-grid land cohorts. The figure is adapted from Stocker et al. (2014). LUC here is similar
 1014 as in Fig. 1, except that forest is no longer a single ageless patch but consists of two patches of primary
 1015 and secondary forests, i.e., having an age structure. (a) The same area of forest is converted to cropland as
 1016 in Fig. 1a but conversion is made from primary forest. (b) Consequently, a ‘young’ cropland patch with
 1017 rich legacy forest soil C is established. In the meanwhile, a very young forest patch is established due to
 1018 the bi-directional gross land flux. Because the model uses multiple sub-grid patches to represent
 1019 vegetation age structure (or differently aged cohorts), merging of patches with different carbon stocks is
 1020 no longer necessary. Subplot (c) shows an alternative to (a) where conversion of forest to cropland is
 1021 made on a secondary forest. Correspondingly, in subplot (d), which shows the post-LUC state of (c), the
 1022 established young cropland patch will have lower legacy soil C than that in (b).
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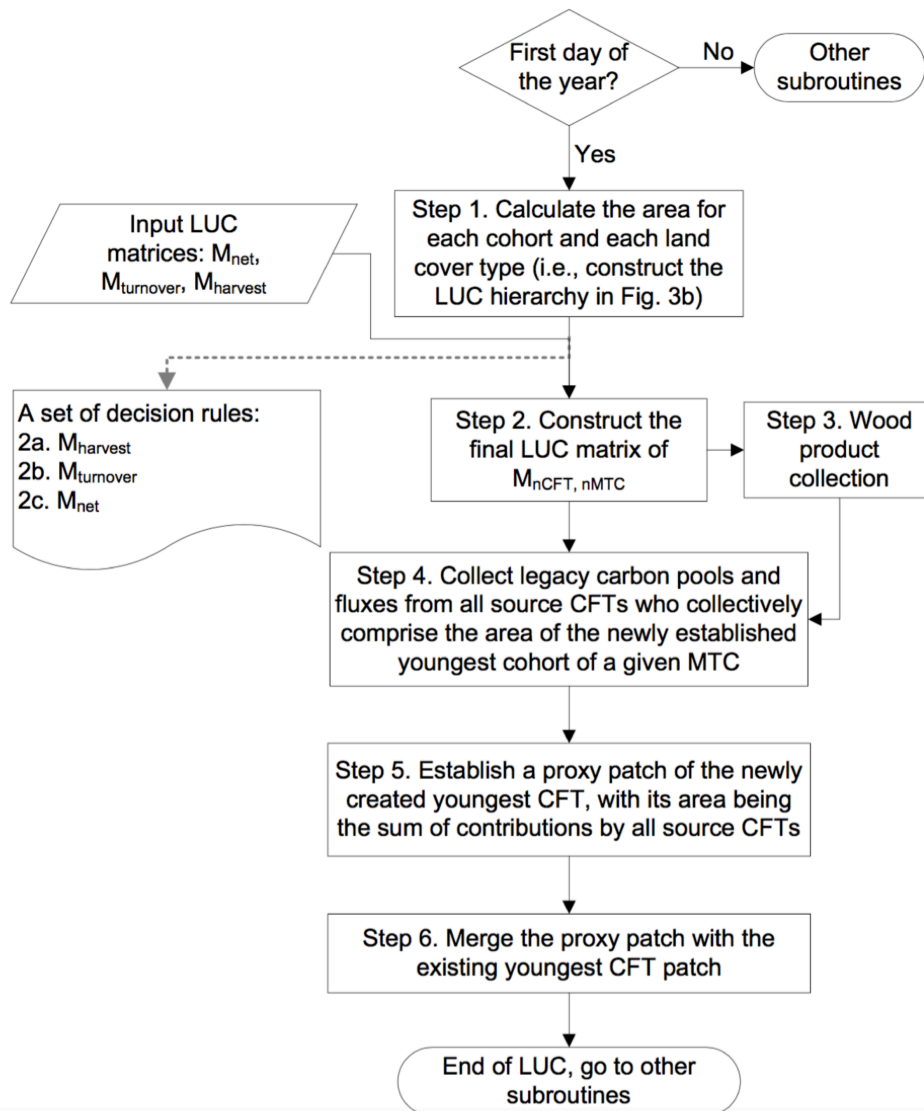
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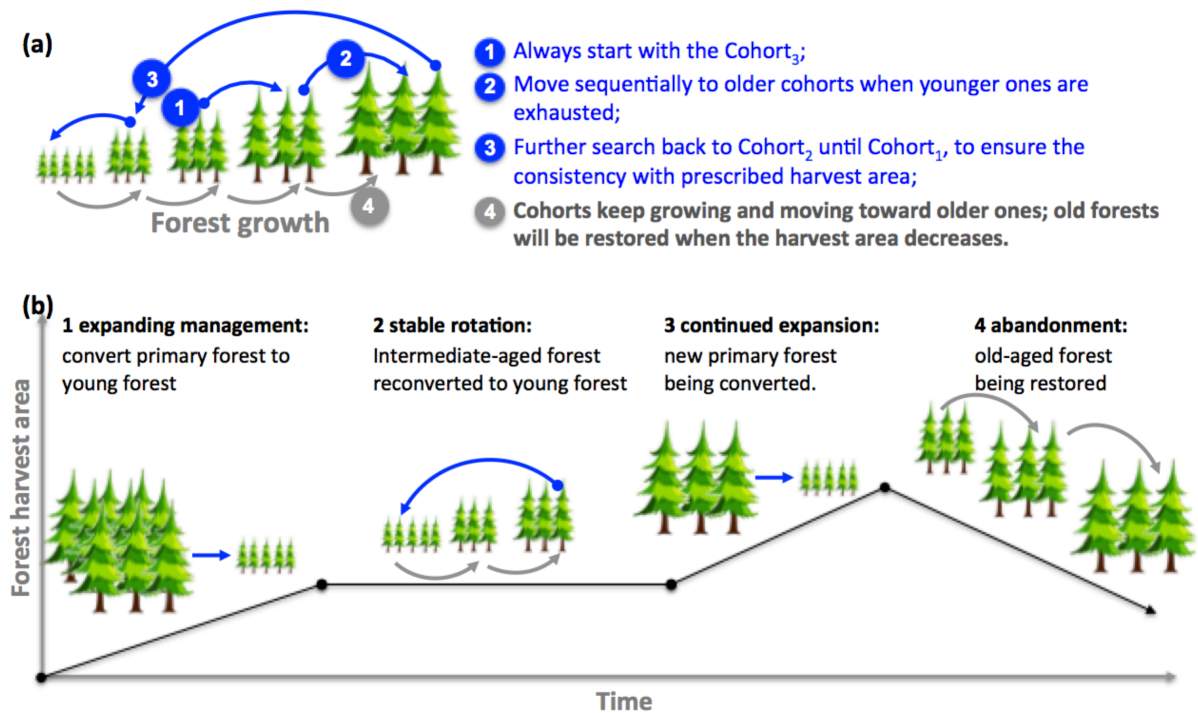
Fig. 3 Two parallel hierarchies from the model parameterization and land use change perspective. (a) Sub-grid cohort function types (CFTs) as inheritances of meta-classes (MTCs) and the corresponding parameterization hierarchy. There are in total 14 vegetative MTCs corresponding to four vegetation types. The notation of CFT_{i,j} indicates that it inherits from MTC_i and belongs to the jth cohort (Cohort_i). Each forest MTC has six cohorts, with Cohort₁ being the youngest and Cohort₆ the oldest, whereas each herbaceous MTC is set tentatively to have two cohorts. Darker colors indicate older cohorts. (b) Within the gross LUC module hierarchy, Tier 3 remains the level of CFT, but CFTs are re-organized to derive the Tier 2 information based on the level of cohorts, under the same Tier 1 as in (a). A cohort bearing the notation of Cohort_{v,i} indicates it belongs to vegetation type 'v' (where 'v' could be forest, natural grassland, pasture and cropland) and meta-class 'i'. This re-organization of the hierarchy from the left to the right side is to prepare for properly allocating prescribed LUC transitions first onto the cohort level, then further to different CFTs within each cohort.



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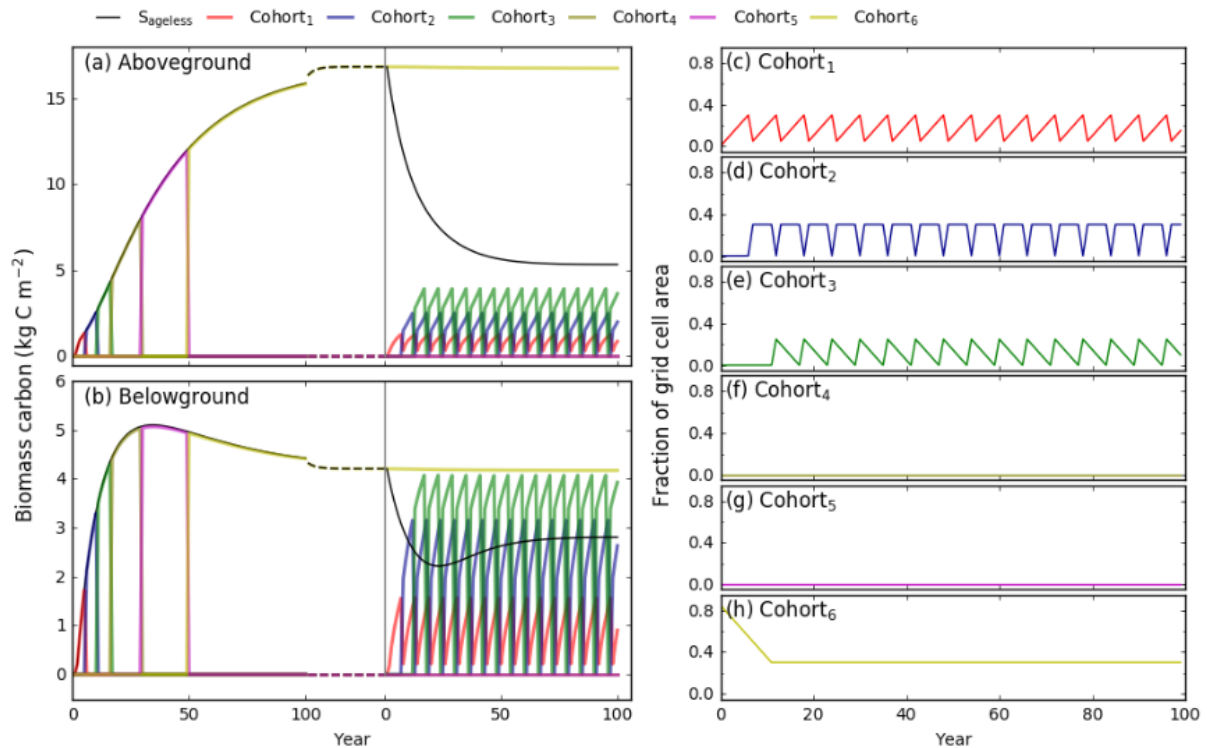
1038 Fig. 4 Schematic representation of the new LUC scheme in ORCHIDEE-MICT v8.4.2 accounting for net

1039 land use change, land turnover and forest harvest in combination with sub-grid cohort representation.

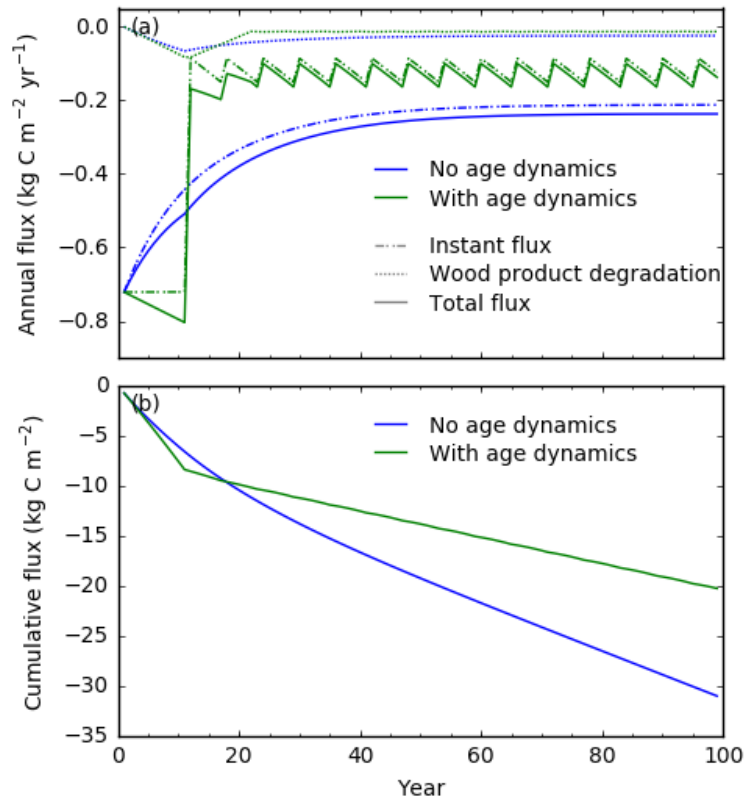


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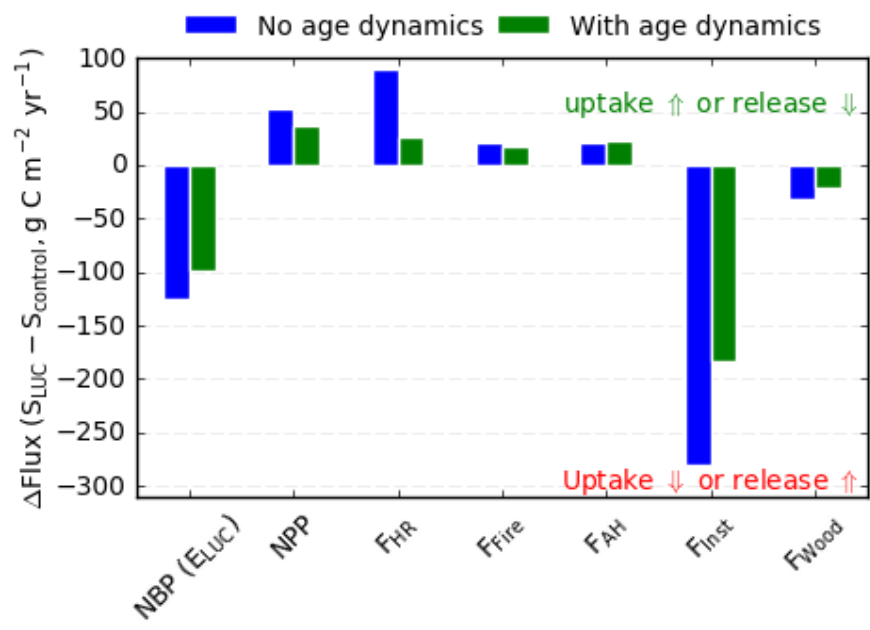
Fig. 5 Rules of selection of forest cohorts in secondary wood harvest to account for the dynamics in harvest area over time. (a) Rules of selection of forest cohorts (blue arrows). Clear-cut harvest (1) first starts with intermediate-aged cohort, then moves to older cohorts until the oldest one; (2) if the prescribed harvested area still cannot be satisfied, then the harvest will move back to the even younger cohorts (3) to the youngest one until the prescribed harvested area is fulfilled. Independent of the harvest activity is the movement of forests from younger cohorts to older ones because of growth (gray arrows). (b) Example of cohort dynamics along with temporal changes in the harvest area shown in the black curve: (1) before the onset of any harvest activity (i.e., after the model spin-up), only the oldest cohorts are available so harvest starts with the primary forest; (2) for a stable harvest area, a steady-state cycle is established involving only secondary forest (intermediate secondary cohorts being harvested is represented by the blue arrow, and younger growing cohorts are represented by gray arrows); (3) then with an increase in harvest area, more primary forests are harvested; (4) finally in this example, the harvest area decreases, and older cohorts are restored.



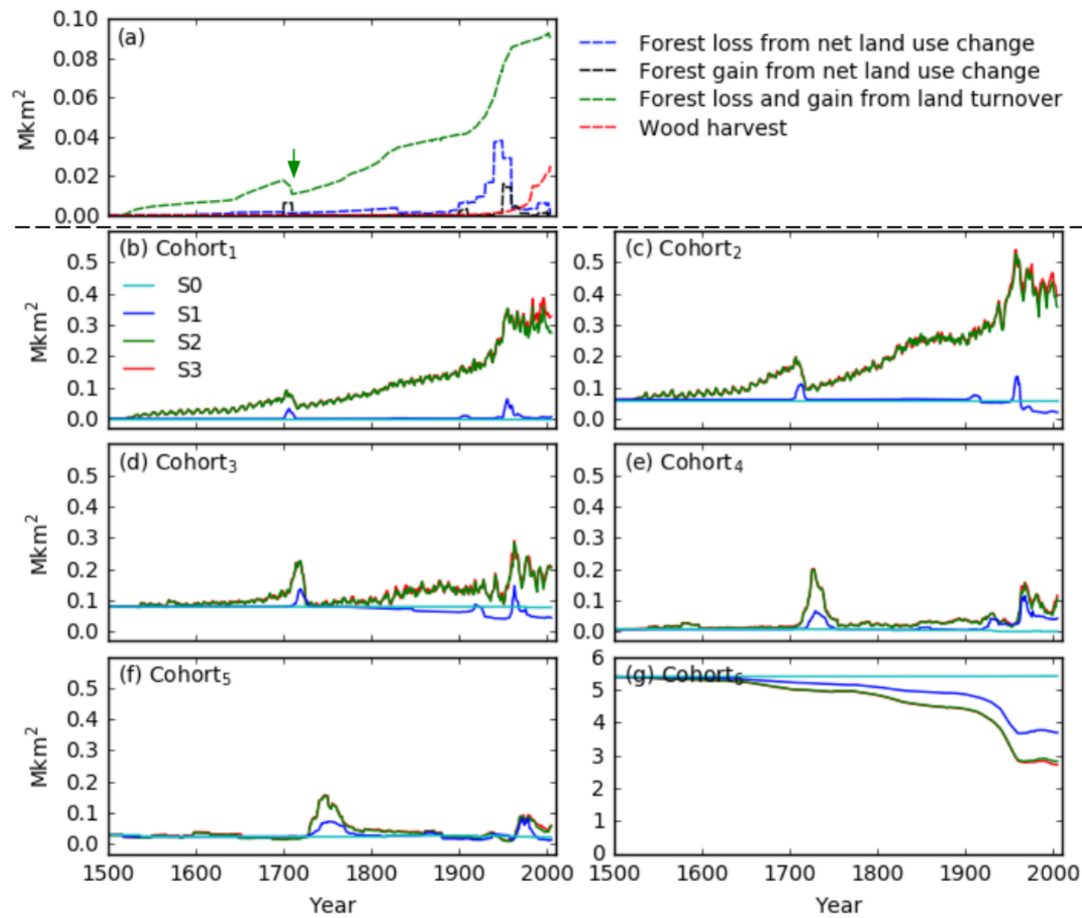
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 1056 Fig. 6 Biomass carbon stock as simulated by two model configurations without (S_{ageless}) and with sub-grid
 1057 age dynamics (S_{age} , comprising of Cohort₁ to Cohort₆) for (a) aboveground biomass and (b) belowground
 1058 biomass. Data shown are the biomass accumulation during the spin-up simulation (which lasts for 450
 1059 years, from Year 0 until the end of dashed line) and transient simulation (which lasts for 100 years) where
 1060 an annual forest-cropland turnover with 5% of the grid cell area is applied. Forest clearing for cropland
 1061 primarily targets at the Cohort₃. Vertical gray lines indicate the end of the spin-up and the start of
 1062 transient simulations. Subplot (c)–(h) show ground coverage by different forest cohorts as fractions of
 1063 grid cell during the transient simulation only.
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 1066 Fig. 7 (a) Carbon fluxes directly associated with LUC (negative values for carbon lost from ecosystems):
 1067 instantaneous flux (dash-dotted line), flux from wood products degradation (dotted line) and the total flux
 1068 (solid line) for simulations with (green) and without (blue) sub-grid age dynamics. (b) Cumulative LUC-
 1069 associated direct fluxes (the sum of instantaneous and wood products degradation fluxes) for simulations
 1070 with (green) and without (blue) sub-grid age dynamics. Data are shown for an annual forest-cropland
 1071 turnover of 5% of the grid cell area for 100 years.
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 1074 Fig. 8 Mean annual carbon flux differences between the LUC and control simulations over 100 years for
 1075 an annual forest-cropland turnover with 5% of the grid cell area for two model configurations: without
 1076 (blue) and with sub-grid age dynamics (green). Positive (negative) values indicate contributions to
 1077 enhanced carbon sink (source) in LUC simulation compared to the control one, either by stronger
 1078 (weaker) carbon uptake or smaller (stronger) carbon release. E_{LUC} is shown as a negative value here, i.e.,
 1079 the LUC simulation has a lower NBP than the control one, indicating an effect of net carbon source by
 1080 LUC.
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Fig. 9 Areas subject to historical land use change and the resulting modeled temporal changes in areas of different forest cohorts in Southern Africa. (a) Areas subjected to historical land use change in which forests are involved. Data are from LUH1 reconstruction (Hurt et al., 2011) after adaptation for ORCHIDEE-MICT. Three types of LUC activities are shown and their effects elucidated by factorial simulations (Table 4). These are: forest loss (blue dashed line) and gain (black dashed line) resulting from net land use change, forest involved in land turnover (both loss and gain in equal amount, green dashed line), and forest area subjected to wood harvest (red dashed line). (b)–(h) Areas of forest cohorts (Cohort₁ = the youngest, Cohort₆ = the oldest) for four factorial simulations (Table 4) where no land use change occurs in S0, and the three LUC types are added in a factorial set-up in S1 (net land use change, blue solid line), S2 (net land use change + land turnover, green solid line) and S3 (net land use change + land turnover + wood harvest, red solid line). Note y-scale values in subplot (a) and (h) differ from others.

1096 Table 1. An over view of DGVMs having implemented gross land use change (shifting cultivation) and forest wood harvest.

Model name	Reference	Shifting cultivation	Wood harvest	Number of vegetation types	Number of secondary land tiles	Secondary vegetation types
LM3V	Shevliakova et al., 2009	Yes	Yes	Crop, pasture, primary and secondary vegetation	Up to in total 12 tiles	Dynamic secondary vegetation type according to the total biomass and prevailing climate
ISAM	Jain et al., 2013; Song et al., 2016	No	Yes	20 PFTs: 10 forests, 2 pastures, 2 grasses, 2 savanna, 1 shrubland, 1 tundra, 2 crops	1 tile for each secondary forest type	Tropical evergreen and deciduous forests, temperate evergreen and deciduous forests, and boreal forest
VISIT	Kato et al., 2013	Yes	Yes	14 PFTs: 8 forests/woodlands, 1 savanna, 1 grassland, 2 shrublands, 1 tundra and 1 cropland	1 tile for each secondary PFT	13 natural PFTs
JSBACH	Reick et al., 2013	Yes	Yes	12 PFTs: 4 forests, 2 shrubs, 2 grasslands, 2 pastures, and 2 croplands	No separate secondary lands	
LPX-Bern 1.0	Stocker et al., 2014	Yes	Yes	10 PFTs: 8 woody, 2 herbaceous	1 tile for each PFT	10 PFTs
LPJ-GUESS	Bayer et al., 2017	Yes	Yes*	9 natural woody PFTs, 2 natural grass PFTs; 3 cropland cohort functional types, 2 pasture PFTs	1 tile per newly created secondary land	Dynamic vegetation type according to prevailing climate and PFT competition
ORCHIDEE-MICT v8.4.2	This study	Yes	Yes	14 PFTs: 8 forests, 2 grasslands, 2 pastures and 2 croplands	Number of tiles parameterizable for each PFT	14 PFTs

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1098 *Wood harvest was not included in Bayer et al. 2017.

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1100 Table 2 A set of implemented rules regarding cohort selection for different land use change processes

LUC process	Cohort decision rule
Primary forest harvest	Start with the oldest cohort, then move to younger ones
Secondary forest harvest	Start with an intermediate cohort (configurable), then move to older ones, and finally to younger ones.
Clearing of forest for net land use change	Start from the oldest cohort, then move to younger ones.
Clearing of forest for land turnover	Start with an intermediate cohort (configurable), then move to older ones, and finally to younger ones.
Conversion of herbaceous vegetation to forests or other vegetation	Start with the oldest cohort, then move to younger ones.

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1102 Table 3. Fractions of aboveground woody biomass lost immediately to the atmosphere during a forest
 1103 clearing, and channeled to 10-year and 100-year turnover wood product pools. These fractions are
 1104 different depending on forest biomes.

	Tropical forest	Temperate forest	Boreal forest
F_{instant}	0.897	0.597	0.597
$F_{10\text{yr}}$	0.103	0.299	0.299
$F_{100\text{yr}}$	0	0.104	0.104

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1106 Table 4 Factorial simulations to examine forest cohort dynamics when including different LUC processes:
 1107 net land use change, land turnover and wood harvest. The plus signs (“+”) indicate that the corresponding
 1108 processes (matrices) are included in the simulations. Only simulations with sub-grid age dynamics are
 1109 done, with $S0_{\text{age}}$ having no LUC activities to $S3_{\text{age}}$ including all LUC processes.

Simulations and LUC processes included

Simulations	Net land use change	Land turnover	Wood harvest
$S0_{\text{age}}$			
$S1_{\text{age}}$	+		
$S2_{\text{age}}$	+	+	
$S3_{\text{age}}$	+	+	+

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