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Generic crop rotation pattern-matching algorithm revealed dominant rotational systems for France

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Abstract

Crop rotations remain poorly documented at large spatial scale, despite their central role in agroecosystem sustainability. We present a generic pattern-matching algorithm to infer crop rotations from annual crop sequence datasets, such as those derived from the European Land Parcel Identification System, with minimal crop aggregation. This method identifies field-level rotations, quantifies their flexibility, and enables spatially-explicit assessment of dominant crop and grasslands rotational systems at various spatial and thematic levels. Applied to mainland France, the approach identified crop rotations on 90% of arable area, with four-year rotations –typically including two to three years of flexible crops– being the most common. Nationally, the top 20 rotations accounted for 30% of arable land, while the top 52 covered 50%. At the agricultural district scale, we distinguished 25 dominant rotational systems grouped into eight categories, including (i) maize grain monocropping, (ii) maize grain – winter wheat rotations, (iii) sunflower – winter wheat rotations, (iv) grass-based systems, (v) maize silage – winter wheat rotations, (vi) winter wheat – barley – rapeseed rotations, (vii) root crop-based rotations, and (viii) specialized production. At national scale, organic rotations were longer and more flexible than conventional ones. Rotations of larger farms were longer and temporally more diverse than smaller ones, but showed lower spatial diversity. This scalable, data-driven approach offers new insights into crop rotation patterns and their spatial variability. It can support the large-scale assessment of agroecosystems with quantitative evidences on dominant rotations, but also help at tracking and characterizing localized rotational innovations.

Keywords

Cropping patterns, Temporal crop diversity, Crop sequences, Crop rotations, Cropping systems, Organic farming, Rotation flexibility

Highlights

- Method to identify and characterize field-level flexible crop rotations
- Rotations identified on 90% of total mainland France arable land
- 52 rotational patterns alone covered 50% of national-scale arable area
- Spatial heterogeneities of rotational systems grouped into 25 clusters
- Rotation length and flexibility indicators supporting farming system assessments

39 1. Introduction

40 Crop rotations are key drivers of farming system sustainability, resilience and climate change
41 adaptation (Dury et al., 2012; Kollas et al., 2015). They shape the spatiotemporal arrangement and
42 diversity of crops across plot, farm, and landscape scales (Castellazzi et al., 2008), thereby influencing
43 yields (Dardonville et al., 2022), input needs -such a pesticide use (Guinet et al., 2023)- and the
44 provision of ecosystem services (Bohan et al., 2021; Duru et al., 2015). Transitioning to longer and
45 more diversified rotations offers multiple benefits: reduced soil erosion, sustained soil fertility and
46 water retention, enhanced biodiversity via improved food and habitat resources, improved nutrient
47 cycling, and disrupted pest and disease cycles (Keichinger et al., 2025; Kollas et al., 2015). Notably,
48 reintroducing legume species and leys into cropping systems offers a promising way to provide a
49 balanced set of ecosystem services while potentially reducing negative agronomic impacts (Cadel et
50 al., 2023; Martin et al., 2020; Nemecek et al., 2008). For example, adding temporal grasslands or ley
51 pastures into rotations can lower the need for mineral fertilizers in following crops, improve soil
52 structure, and enhance biological pest control (Meiss et al., 2010; Zhao et al., 2022). However, the
53 adoption of such strategies remains limited due to constraints in machinery, technical expertise, and
54 perceived economic risk (Dury et al., 2012; Meynard et al., 2018; Steinmann and Dobers, 2013).

55 Quantitative evidences on actual crop rotation implemented by farmers, and what dominant patterns
56 emerge at landscape or regional scales (e.g., rotation type, length, flexibility, etc.), remains scarce
57 (Reumaux et al., 2023). However, spatially explicit rotation data are essential for diagnosing and
58 assessing cropping systems, and for designing policy interventions based on localized evidences (Bohan
59 et al., 2021). At the local scale, crop rotations are commonly estimated via expert knowledge, field
60 surveys or farmer interviews (Xiao et al., 2014). Yet, these methods are difficult to scale for regional or
61 national analysis, such as evaluating ecosystem services from agriculture (Tibi and Therond, 2024) or
62 estimating cropland carbon storage potential (Launay et al., 2021). Large-scale assessments often rely
63 on simplified crop rotation simulations due to computational and data limitations (Barbieri et al.,
64 2017), still requiring robust methods to identify representative rotations (Schönhart et al., 2011).
65 Critically, the selection and spatial allocation of simulated rotations substantially influences
66 assessment outcomes, shaping both conclusions and policy recommendations (Sahajpal et al., 2014;
67 Sharp et al., 2021).

68 Access to field-level crop sequences is a prerequisite for identifying crop rotations. Following the use
69 of survey data on land use (e.g., TERUTI-LUCAS; Ballot et al., 2023; Xiao et al., 2014), advances in
70 remote sensing and dedicated geographic information systems have made it possible to obtain annual
71 records of crops grown on arable land over consecutive years (*crop sequences*) in several regions,
72 including the European Union, Great-Britain and China (Blickensdörfer et al., 2022; Upcott et al., 2023).
73 For example, multi-annual datasets derived from the European Land Parcel Identification System (LPIS)
74 have been used to document crop sequences for nearly 8.5 million French agricultural plots
75 continuously since 2015 (Levvasseur et al., 2016), covering approximately 94% of the country's
76 agricultural area (Dedieu et al., 2024; Girault and Martin, 2024).

77 However, the intrinsic diversity of crop sequences presents a major challenge (Stein and Steinmann,
78 2018). Theoretically, up to 100^4 unique crop sequences can be observed over four years in a system
79 involving 100 different crops (Sahajpal et al., 2014). This diversity reflects the influence of
80 unpredictable, context-specific factors on annual cropping decisions -such as weather, market
81 conditions, and contractual constraints (Bohan et al., 2021; Sharp et al., 2021; Upcott et al., 2023).
82 Even when rotations are planned, they are rarely fixed (i.e., a strict, recurring crop order). Adjustments
83 and substitutions are common, leading to flexible -even non-cyclical- rotations of variable length
84 (Castellazzi et al., 2008).

85 Previous efforts to characterize crop rotations at large scales typically addressed this diversity by
86 simplifying crop sequences: grouping crops into broad categories (often 10-20 types), limiting the
87 temporal scope to less than 4-5 years, or narrowing spatial coverage (Upcott et al., 2023). Rotation
88 identification methods fall into two main categories: indirect and direct. Indirect methods apply
89 statistical techniques -such as Markov models or clustering- to generate synthetic, yet territorially
90 representative, crop rotations. These are then assessed with agronomic expertise (Dupuis et al., 2022;
91 Mignolet et al., 2007; Nowak et al., 2022; Sharp et al., 2021). In some cases, analysis of the crop
92 sequence structure, using frequency and diversity metrics, is performed (Ballot et al., 2023; Burchfield
93 et al., 2024; Reumaux et al., 2023; Stein and Steinmann, 2018). Shorter crop sequences are eventually
94 assumed to be cyclical by default (Mairura et al., 2022; Plourde et al., 2013). Direct methods, in
95 contrast, search for recurring patterns within individual crop sequences and assess their
96 representativeness post hoc (Leenhardt et al., 2012; Steinmann and Dobers, 2013; Upcott et al., 2023).
97 While these approaches preserve the initial spatial resolution, like field scale, they face challenges in
98 algorithmic convergence, as strict crop rotations are generally rare.

99 We present here a novel, generic, and tunable method to identify crop rotation patterns from field-
100 level crop sequence datasets, explicitly accounting for their flexibility. Using mainland France as a case
101 study, we demonstrate its ability to characterize cropping systems through rotation patterns and
102 support large-scale assessments. First, we identify dominant crop rotations at the national level and
103 reveal subnational specialization at the agricultural district scale. Second, we analyze how crop
104 rotations attributes –such as length, flexibility, and types– vary across cropping systems (organic vs.
105 non-organic) and farm sizes. Given access to crop sequence data, this approach is readily applicable to
106 other regions and scales, offering analytical insights beyond the current case study. It supports both
107 macro-level analyses, such as identifying dominant rotations across broad areas, and micro-level
108 investigations, such as tracking the adoption of innovation practices or the integration of specific crops
109 into localized rotational systems.

110 2. Materials and method

111 2.1. Flexible crop rotation pattern-matching algorithm

112 We developed a novel method for identifying and classifying crop rotations, extending the rule-
113 based approach from Leenhardt et al., (2012). The method targets cyclical crop rotations of fixed
114 length, following the classification by Castellazzi et al., (2008). It requires two inputs: a crop sequence
115 dataset and a crop codes nomenclature. The crop sequence dataset contains, for a given geographical
116 area the ordered list of N successive crop names/codes recorded on each agricultural plot (hereafter
117 referred to as *field*). These temporally ordered lists of length N are referred to as *observed sequences*.
118 Prior to rotation identification, the dataset undergoes specific pretreatments.

119 2.1.1. Crop sequence pretreatment

120 Observed crop sequences are initially described with the native crop classification of the source
121 data, which may be unsuitable for agronomic analysis. For example, the post-2014 French LPIS datasets
122 use a nomenclature of more than 300 crop codes, originally designed for the Common Agricultural
123 Policy (CAP) subsidies estimation, potentially leading to artificially high sequence diversity. A crop
124 codes simplification table can be used to aggregate these native codes to a coarser, goal-oriented
125 resolution, enhancing the detection of recurring patterns in simplified sequences. Aggregation can be
126 based on agronomical similarity, for example. Previous studies typically used a simplified classification
127 prioritizing major crops and grouping minor ones into broader classes (e.g., grouping all cereals except
128 soft wheat and barley under “other cereals”), leading to 10-20 types (benchmark in the **Supplementary**
129 **Materials; SM**). In our case study, we applied a refined nomenclature of 41 crop codes, enabling more

130 detailed agronomic assessment (**Table 1**). Only fully characterized sequences -those without missing
 131 values nor ambiguous “diverse” entries-, without perennial crops, were retained for the rotation
 132 identification step (see **Section 2.2.2**).

133 **Table 1: Crop codes nomenclature**

Crop code	Full name	Crop category
ORH	Winter barley	Cereals
ORP	Spring barley	
RIZ	Rice	
SGH	Winter ray	
SGP	Spring ray	
SOG	Sorghum	
TTH	Winter triticale	
TTP	Spring triticale	
AVH	Winter oat	
AVP	Spring oat	
BDH	Winter durum wheat	
BDP	Spring durum wheat	
BTH	Winter (common) wheat	
BTP	Spring (common) wheat	
cer2nd	Other cereals	Oilseeds
CZH	Winter rapeseed	
CZP	Spring rapeseed	
TRN	Sunflower	
olea	Other oilseeds	Legume leys
prairieA	Legume leys	
gel	Fallow land	
prairie	Grass	
foua	Fodder roots	Root crops
PdT	Potato	
BTN	Sugar beet	
CHV	Hemp	Other
LIF	Fiber flax	
legfl	Horticulture	
aindus	Other industrial crops	
MIE	Maize silage	Maize
MIS	Maize grain	
lupH	Winter lupin	Pulses
lupP	Spring lupin	
poisH	Winter pea	
poisP	Spring pea	
SOJ	Soybean	
FVL	Field bean	
leggr	Other pulses	
div	Diverse	
cann	Sugarcane	

134 Mapping of 352 native LPIS crop codes with the proposed 41 crop codes nomenclature is provided in the **Supporting Data**
135 (Javourez, 2025).

136 2.1.1.2. Pattern matching algorithm

137 Rotation identification is performed by systematically detecting and classifying recurrent patterns
138 within each observed crop sequence. A pattern (P_n) is defined as a subsequence of n consecutive crops
139 that repeats -either fully or partly- within an observed crop sequence of fixed length N . Repetitions
140 may be separated by crops not included in the pattern, referred to as *non-P*. Patterns may include
141 repeated instances of the same crop and are not restricted in diversity. For example, in the observed
142 sequence A_B_B_D_A_B_B_A ($N = 8$; with each letter representing a distinct crop), the recurrent
143 pattern $P_n = A-B-B$ appears twice. Here, *non-P* = {D}, as crop D separates the two repetitions. For each
144 unique observed sequence, all *possible patterns* P_n , where n ranges from 1 to n_{max} , are initially
145 considered. n_{max} is the maximum pattern length evaluated.

146 A pattern is retained as a *matching pattern* only if it covers a minimum length threshold percentage
147 ($\%seq_{min}$) of the observed sequence. For a sequence of length $N=8$, setting $\%seq_{min}$ to 60% means a
148 pattern must cover at least 5 years ($5/8 = 62.5\% \geq 60\%$). When computing the sequence coverage
149 ($\%seq$), potential truncation at the beginning or end of the observed sequences is accounted for. In the
150 previous example, pattern A-B-B is observed twice. The presence of crop A at the end may indicate a
151 third repetition, or at least does not preclude it. Therefore, A_B_B is considered to cover 7 of 8 years,
152 yielding $\%seq = 88\%$, and is classified as a matching pattern. This tolerance allows to capture flexibility
153 in crop rotations: patterns need not to fully or exactly cover the sequence; a share of *non-P* crops is
154 permitted as long as coverage exceeds $\%seq_{min}$.

155 The $\%seq_{min}$ threshold is tunable but must be strictly greater than n_{max}/N to ensure that matching
156 patterns occur at least twice (including possibly truncated repetitions) within the sequence. As a
157 default, we recommend setting n_{max} to no more than $N/2$. For instance, in 8-year crop sequences
158 limiting pattern length to a maximum of four years allows for at least two full repetitions to be
159 theoretically observable (limits in **Section 4.1**). Multiple matching patterns (e.g., of two and four years)
160 may be identified for a single crop sequence, but only one is retained based on a hierarchical selection
161 procedure. First, patterns with the highest length sequence coverage ($\%seq$) are prioritized. In case of
162 ties, the shorter-length matching pattern is selected. If ties persist, the pattern appearing later in the
163 sequence -i.e., more recently in time- is favored.

164 Each sequence with a selected pattern is classified using a custom notation: $*P_n_f_{non-P}_{\%seq}$
165 where P_n is the selected pattern, *non-P* the list of flexible (*f*) crops between its repetitions, and $\%seq$
166 its coverage. These are referred to as *classified sequences*. To harmonize the classification, a circularity
167 check is applied: patterns that are circular permutations of each other (e.g., A-B-C, B-C-A, C-A-B) are
168 renamed to a common canonical form (e.g., A-B-C, for being the first occurrence). Similarly, the
169 associated *non-P* lists are standardized within each unique pattern. Revisiting the sequence
170 A_B_B_D_A_B_B_A (with $\%seq_{min}=60\%$ and $n_{max}=4$), eight matching patterns are identified: (i) A-
171 B_f_{B-D, B}_62%, (ii) A-B-B_f_{D}_88%, (iii) D-A-B_f_{B, B-A}_62%, (iv) A-B-B-D_f_{A-B-B}_62%, (v) B-
172 B-D-A_f_{B-B-A}_62%, (vi) B-D-A-B_f_{B-A}_75%, (vii) D-A-B-B_f_{A}_88%, and (viii) A-B-B-A_f_{B-B-
173 D}_62%. Patterns (ii) and (vii) both reach the highest sequence coverage (88%). Pattern (ii) is selected
174 due to its shorter length (three vs. four years). Not all sequences yield matching patterns, even when
175 they contain repeated crops. For example, sequences such as A_B_C_D_E_B_A_D and
176 A_A_A_A_B_B_B_B do not satisfy the matching criteria under the above algorithm settings.

2.1.3. Selection of dominant crop rotations

Following terminology harmonization, the diversity of classified $*P_n_f_{\{non-P\}}\%seq$ objects can remain substantially high, depending on the sequence length (N), algorithm settings, and the characteristics of the studied area (e.g., spatial extent, crop diversity, etc.). At this stage, each unique selected patterns P_n is treated as a *potential crop rotation*. This is justified by the algorithm's focus on identifying patterns based on their recurring propensity. However, these patterns are not necessarily observed as fully covering any observed sequence (i.e., $\%seq < 100\%$) and may not be strictly repeated in practice. Therefore, they remain *potential* until further evidences support their agronomic feasibility and representativity.

The broader the area over which a *potential* rotation was selected as a matching pattern, the more likely it appeared under varying conditions (e.g., with different flexible crops or temporal arrangements), gaining support as a *representative crop rotation* of the studied area. Since each classified sequence is linked to a single selected pattern P_n , the cumulated area coverage of each potential rotation can be ranked. This ranking enables the identification of *dominant crop rotations*. The threshold for defining representativity is subjective and should align with the study's objectives. For instance, dominant rotations may be defined as the selected patterns P_n either covering at least a minimum share of the total arable land, belonging to a predefined maximum number of rotations, or collectively summing over a target cumulative area coverage (Sahajpal et al., 2014). *Crop rotations* further refer to selected patterns (P_n) that meet the predefined thresholds for representativity, while flexible crops (*non-P*) and sequence coverage ($\%seq$) are treated separately, as flexibility attributes.

2.1.4. The case of near-monocropping

Length-one crop rotations (P_1), as identified by the pattern-matching algorithm, include both strict and near-monocropping. Merging these categories when analyzing rotational systems can lead to agronomic inconsistencies and misinterpretations. For example, near-monocropping of winter wheat -occurring 5-6 times over 8 years- is relatively common in France, whereas strict monocropping is rare. Here, strict and near-monocropping practices are distinguished by combining length-one patterns with their sequence coverage, noted as $P_1_ \%seq$, when ranking *potential* crop rotations. For other patterns (P_n , with $n \neq 1$), only P_n was considered (see **section 2.1.3**). Examples of near-monocropping identified using the algorithm include the sequences A_A_A_A_A_B_B_A and A_B_A_C_A_D_A_A. These are classified as $A_f_{\{B-B\}}75\%$ and $A_f_{\{B, C, D\}}62\%$, respectively, and the resulting crop rotations are denoted A_75 and A_62 . However, as defined, a near-monocropping identified as dominant across the study area -e.g., A_75 - remains implicit and cannot be directly simulated by soil-crop models. Although not mobilized in the case study, we propose an approach to reconstruct artificial, explicit N -year crop rotations representative of each near-monocropping, enabling simulation. This reconstruction relies on identifying the most frequent flexible crops (*non-P*) associated with a given near-monocropping and inserting them between repeated sequences of the dominant crop (of typical length), following study area-level statistics (see **SM**).

2.1.5. The case of grass-crop mixed patterns

An additional treatment targets non-classified sequences involving temporary grassland-based rotations (i.e., including grass and legume leys). The objective is to identify extended rotational patterns ($n > n_{max}$) that include consecutive years of temporary grassland and other crops. Non-classified sequences containing at least $100 - \%seq_{min}$ consecutive years of grass codes (from the grass category; see **Table 1**) are retained. For $N=8$ and $\%seq_{min} = 60\%$, this corresponds to sequences with 3-4 years of consecutive grassland. The algorithm then searches within the remaining (non-grass) portion of each sequence for any previously identified matching patterns P_n from earlier treatments described above. If a match is found, the same hierarchical selection rules are applied. The sequence is then

223 reclassified with the associated pattern grass-grass-...-grass- P_n . Circular permutations check and
224 terminology harmonization are applied as previously described. This approach likely results in
225 classifying fields undergoing conversion between permanent grassland and arable land as grass-crop
226 mixed rotations (see **Section 4.1**).

227 2.2. Mainland France simulation plan and treatments

228 2.2.1. Data sources

229 We used the 2015-2022 crop sequence dataset developed by Girault and Martin, (2024),
230 derived from public French LPIS data (IGN, 2025) with method detailed in Levavasseur et al., (2016).
231 This dataset documents approximately 14 million elementary plots, resulting from spatial intersection
232 of eight annual LPIS layers, covering 28.2 million hectares (Mha) across the agricultural area of
233 mainland France, including Corsica. Only plots larger than 0.5 hectares were retained, a standard
234 threshold to reduce noise from spatial intersection processes (Levavasseur et al., 2016). After filtering,
235 the dataset includes 8,413,741 plots, hereafter considered as *agricultural fields*, totaling 27.2 Mha
236 (3.5% area loss). This public crop sequence dataset was joined with a restricted-access French LPIS
237 dataset available to researchers, which adds field-level information such as organic farming and farmer
238 identifiers for the same 2015-2022 period (see **SM**).

239 To enable spatial analysis, we discretized mainland France into the 433 historical agricultural districts
240 -established in 1946- provided and used by the French agricultural statistics agency (Agreste, 2017).
241 Their spatial extent varies considerably: filtered crop sequence areas per district range from 0.8 kha to
242 569.1 kha, with a mean of 62.9 kha and a median of 36.4 kha (excluding the *Paris* district with no
243 agricultural land). District assignment was performed via zip code matching between the crop
244 sequence dataset and the reference district table.

245 2.2.2. Algorithm implementation

246 The flexible crop rotation pattern-matching algorithm was applied to the prefiltered and enriched
247 crop sequence dataset for mainland France, using agricultural districts as the reference spatial units.
248 While the zoning does not influence algorithm outputs, it provides a consistent framework for analysis,
249 interpretation and visualization. As the dataset spans $N=8$ years (2015-2022), the maximum rotation
250 length was set to $n_{max} = 4$ years, with a minimum sequence coverage threshold of $\%seq_{min} = 60\%$. It
251 means that matching patterns must cover at least 5 out of the 8 years. A four-year pattern is then
252 considered as a match if it is fully observed at least once within the 8-year period, and either the
253 beginning or end of the pattern is observed on at least one additional year.

254 The about 300 native LPIS crop codes were simplified into a 41-code nomenclature, grouped into 9
255 crop categories (**Table 1**). Agricultural fields (i.e., prefiltered crop sequences) were considered
256 *permanent grassland* if they hosted grass crops continuously across the full 2015-2022 period. Under
257 this definition, permanent grassland accounted for 8.8 Mha or 32.4% of prefiltered area. Crop
258 sequences excluded during pretreatments represented 2.6 Mha (9.5%). It included approximately 0.6
259 Mha (2.1%) of sequences containing at least one perennial crop (e.g., orchards, vineyards) and 2.0 Mha
260 (7.4%) with sequences either incomplete (e.g., missing year) or containing at least one “diverse” code.
261 The remaining 15.8 Mha (58.1%) were classified as *arable land* and constitutes the analysis dataset
262 (4,806,679 fields). The algorithm and the scripts used for the French case study are available, see the
263 **Research data statement**.

264 2.2.3. Spatial, farm and rotation analysis

265 The characterization of rotational systems across France followed the clustering approach of Xiao
266 et al., (2014), with minor adaptations. Agricultural districts were grouped based on the similarity of
267 their dominant crop rotation distributions. First, districts dominated by non-arable land were excluded.

268 Two filtering conditions were applied: (i) a minimum of 20% arable land (as a share of prefiltered area),
269 or (ii) at least 1,000 ha of arable land if arable land was below 50%. This removed 98 districts, which
270 together accounted for only 2.2% of total arable land in mainland France (approx. 0.35 Mha). Next, all
271 crop rotations covering at least 1% of the arable land in any of the 335 remaining districts were
272 retained. For each district, the shares of arable land occupied by these rotations (ranging from 0 to 1)
273 served as active clustering variables (available in the **Supporting Data**; Javourez, 2025). As
274 supplementary variables, we included the average 2015-2022 agricultural land cover per district,
275 expressed using the 41 crop-code nomenclature (**Table 1**). A principal component analysis (PCA) was
276 first performed on the active variables. The top components explaining 95% of cumulative variance
277 were retained for hierarchical clustering, using Ward's method. The workflow was implemented with
278 the FactoMineR package (Lê et al., 2008). The number of PCA dimensions and clusters was manually
279 defined through iterative testing to ensure meaningful spatial differentiation of rotational systems and
280 robust cluster interpretation. Lowering the variance threshold below 95% led to an overrepresentation
281 of grassland-dominated districts in small, poorly interpretable clusters, due to the strong influence of
282 the first grass-related PCA dimension.

283 Cluster analysis included summary statistics of dominant crop rotations within each cluster, along with
284 v -values for both active and supplementary variables. The v -value measures the standardized deviation
285 of a cluster's mean from the overall population mean, and is accompanied by a p -value indicating
286 statistical significance. Typical districts representing each cluster were selected among the five closest
287 to the cluster centroid.

288 To compare conventional vs. organic rotations, fields were classified as *organic* only if continuously
289 declared under organic management throughout the 2015-2022 period. This yielded 0.44 Mha of
290 organic arable sequences (2.8% of total arable land), compared to 1.68 Mha (10.6%) recorded as
291 organic in 2022. To evaluate crop rotations at the farm level, agricultural districts related to permanent
292 grasslands or specialized southwestern France production systems were excluded (Clusters 11, 12, 24,
293 25; see **Section 3.2.**). Among the remaining 278 districts, only farms with at least 20% of their total
294 agricultural area as arable land were included. This selection yielded 175,560 farms (~56% of total
295 farms) accounting for 14 Mha, or ~89% of the total arable land. Farms were then categorized into five
296 size groups based on total prefiltered agricultural area: <20 ha, 20-50 ha, 50-100 ha, 100-200 ha, and
297 >200 ha, consistent with the French agricultural census classification. A separate group for larger farms
298 was not included, as only 16 of the selected farms exceeded 1,000 ha.

299 Temporal crop diversity on arable land was assessed using the Inverse Simpson Index, following Dedieu
300 et al., (2024). This index reflects the effective number of distinct crops in a sequence, weighted by their
301 relative abundance (true diversity of order 2; Keichinger et al., 2025). For 8-year crop sequences, the
302 index ranges from 1 (strict monocropping) to 8 (eight different crops each observed once). Field-level
303 indices were calculated at both the 41 crop-code level (*inv_sim*) and the 9 crop-category level
304 (*inv_sim_cat*), the latter reflecting functional or taxonomic diversity. Here, the spatial diversity of
305 arable land was not directly calculated, but it intrinsically related with its temporal diversity (Bohan et
306 al., 2021). For all classified sequences, rotation length (n) and sequence coverage (*%seq*) were
307 recorded. Aggregated indicators for larger spatial or thematic groups were calculated as area-weighted
308 averages.

309 3. Results

310 3.1. French arable land described by a few yet flexible crop rotations

311 Field-level crop rotations were identified on 14.1 Mha, accounting for ~90% of the 15.8 Mha
312 of arable land in mainland France. This high identification rate was largely achieved by considering

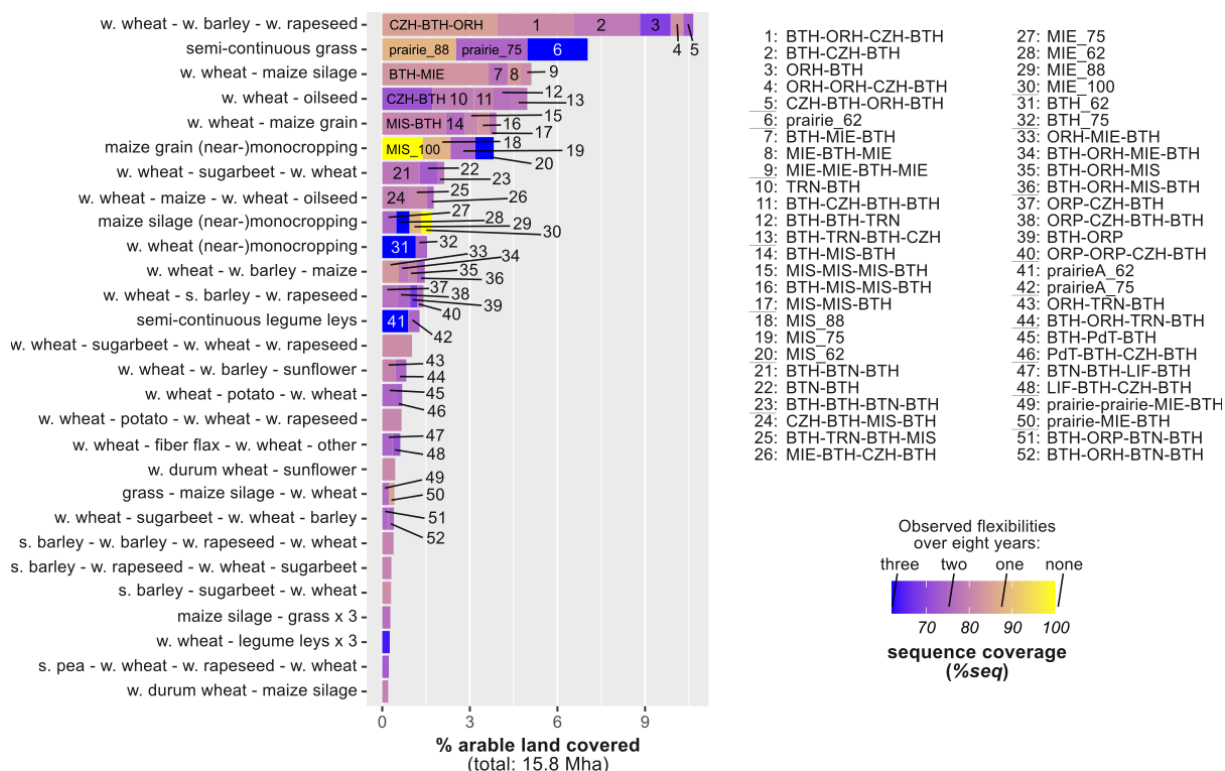
313 flexibilities in crop rotations. Strict monocropping and strict rotations together represented only 9% of
314 arable land, indicating that most fields follow a general rotational structure while allowing for
315 temporary deviations. Over the eight-year observation period, 17% of the arable land exhibited one
316 year of flexibility, 29% showed two, and 31% three. These proportions highlight the role of the
317 sequence coverage threshold in capturing rotational patterns. The most frequent configurations were
318 four-year rotations with two or three flexible years, covering 4.6 Mha (29%), suggesting an overall
319 rotational diversity at field scale. These may include longer underlying cycles not fully detected with
320 the current settings. Integrating the grass-crop mixed treatment (see **Section 2.1.5.**) extended the
321 identification of rotations to an additional 2% of arable land (0.33 Mha). However, such grass-crop
322 mixed rotations were characterized with a high uniqueness (median surface area of 3.9 ha), mostly
323 because of their longer length (area-weighted average of 7.22 years). Hence, this additional treatment
324 yielded limited additional analytical insights.

325
326 At the national scale, the area-weighted temporal crop diversity index (*inv_sim*) for near-
327 monocropping averaged 1.66. This increased to 2.7, 3.1, and 3.3 for two-, three-, and four-year flexible
328 rotations, respectively. A similar trend was observed at the crop category level, although both two-
329 and three-year rotations shared the same diversity (*inv_sim_cat* = 2.1). This indicates a predominant
330 use of two crop categories -typically cereals and oilseeds-, and a limited number of crops in these
331 flexible rotations. Notably, crop diversity tends to increase as both rotation's length and flexibility
332 increase (see **SM**). The 10.4% of arable land with unclassified crop sequences showed notably higher
333 diversity, averaging five different crops over eight years (*inv_sim* = 4.2). This further supports the
334 method's effectiveness in capturing prevalent patterns, with the remaining areas likely reflecting
335 complex, more diversified or transitional cropping systems.

336
337 A relatively small number of rotational patterns dominates the national landscape (**Figure 1**). The 20
338 most common patterns cover 30% (4.7 Mha) of total arable land area, while the top 52 account for
339 50%. Thus, using a 41-crop-code nomenclature, 52 distinct crop rotations are enough to describe half
340 of France's arable surfaces. Beyond the 110th ranked rotation, each represent less than 0.1% of the
341 total: their representativity drops. Many rotations differ only slightly -often by the substitution or
342 addition of a single crop from the same family or season. These are referred to here as *derivatives*. A
343 notable example is the winter wheat – winter barley – winter rapeseed rotation (*w-b-r*), alone
344 identified on 624,000 ha. *W-b-r* derivatives frequently involve additional winter wheat, either
345 consecutively or in alternation. Collectively, the *w-b-r* and its derivatives represent the most
346 widespread rotational group, identified on over 10% of arable land (1.7 Mha). On average, *w-b-r*
347 rotations include one flexible year within an eight-year span (area-weighted sequence coverage ~88%),
348 while derivatives trend toward two (**Figure 1**). Other dominant systems include flexible alternation of
349 winter wheat with maize silage, winter oilseeds, or maize grain. Among these, winter wheat – rapeseed
350 rotations were more flexible (2.2 years on average) than winter wheat – sunflower (1.7 years). Strict
351 monocropping (*inv_sim* = 1.0) covered approximately 2% of arable land (320,000 ha), primarily maize
352 grain (MIS; 220,000 ha) and maize silage (MIE; 60,000 ha), which together represented 87% of this
353 category. The remainder strict monocropping included legume leys (as the pluriannual crop alfalfa),
354 horticulture, and industrial crops (e.g., hop, spice, lavender).

355
356

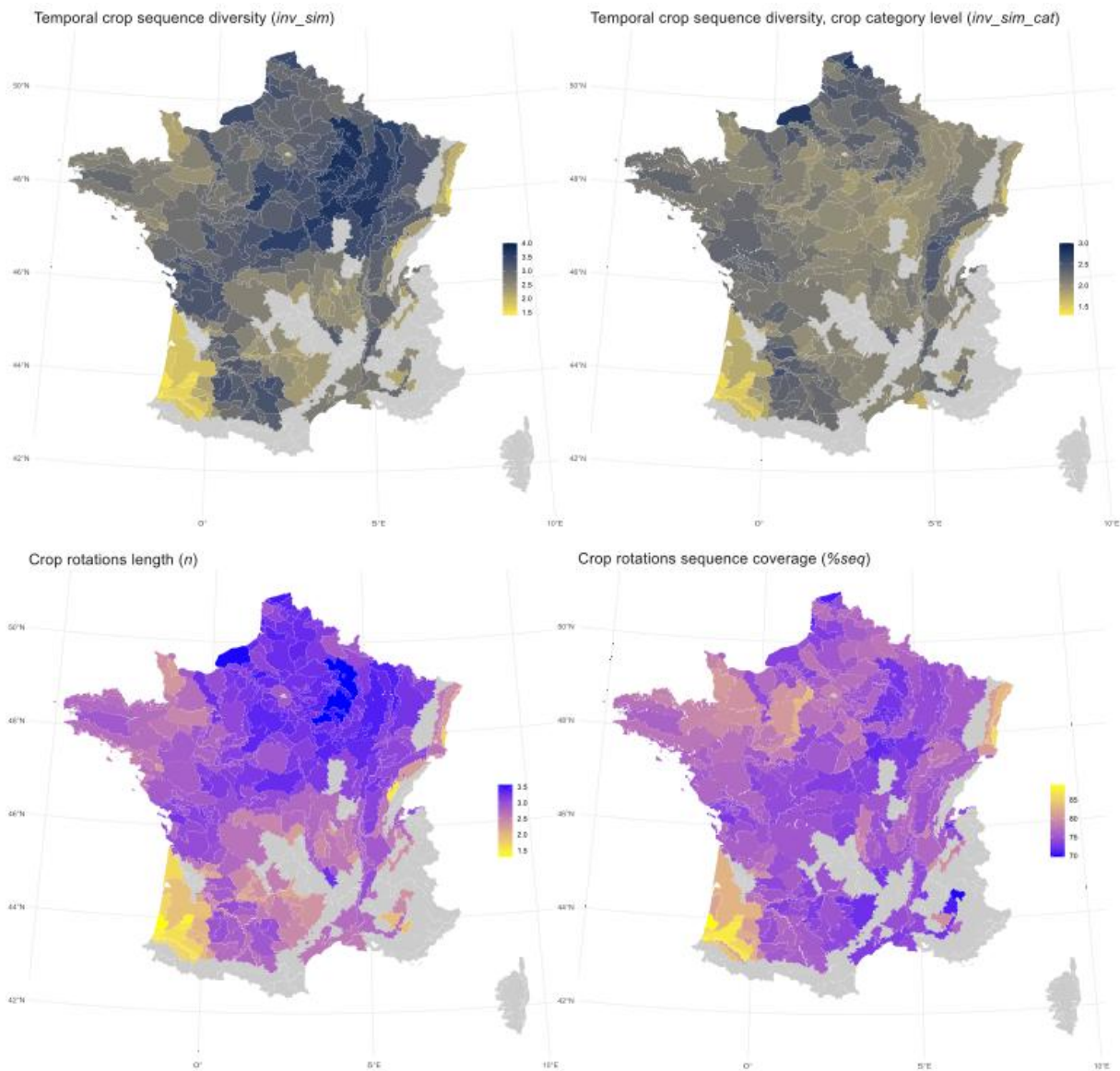
357 **Figure 1: Dominant crop rotations for mainland France**



358

359 Only crop rotations identified on more than 30 kha are displayed here. Derivates around similar rotational patterns were
 360 manually grouped together, and classified by descending coverage of national-scale arable land. The color scale represents
 361 the area-weighted average of field-level sequence coverage %seq per rotation (88% means the rotation presented one year
 362 of flexibility over 8 years; see Section 2.1.2.). Crop codes correspondence is described in Table 1 (w. for winter, s. for spring).
 363 **Supporting data** is provided in Javourez, (2025).

364 **Figure 2: Field-level crop diversity and rotations indicators for mainland France arable land**



365
366 Field-level indicators were averaged at the agricultural district level (area-weighting). Diversity indicators (top) include all
367 arable land crop sequences, while rotation indicators (bottom) only include arable land where crop rotations were identified.
368 Light grey agriculture districts are those presenting a total arable land area below threshold (see **Section 2.2.3.**); these are
369 mostly covered by permanent grassland or perennial crops (e.g., orchards, vineyards). The time scope is 2015-2022 (8 years).
370 **Supporting data** is provided in Javourez, (2025).

371

3.2. Spatial typology of French rotational systems

The analysis at the agricultural district level revealed distinct regional patterns in crop rotations (**Figures 2 and 3**). Despite wide variation in agricultural orientation -arable land covered a median of 59% of the prefiltered area (interquartile range: 27%-79%)- rotation identification rates remained consistent (median: 89%; interquartile range: 86%-92%; see **SM**). Across the 335 arable land-dominated districts used for clustering (see **Section 2.2.3**), the top 10 dominant rotational patterns accounted for an average of 43% of arable land (median: 41%; interquartile range: 34%-50%), indicating that a limited number of rotations can also describe district-level rotational systems. However, these representative rotations varied across clusters: capturing the first 50% of arable land in each district required 758 distinct rotations -compared to only 52 at the national level. Of these, only 372 appeared on at least 1% of the arable land in any of the 335 selected districts.

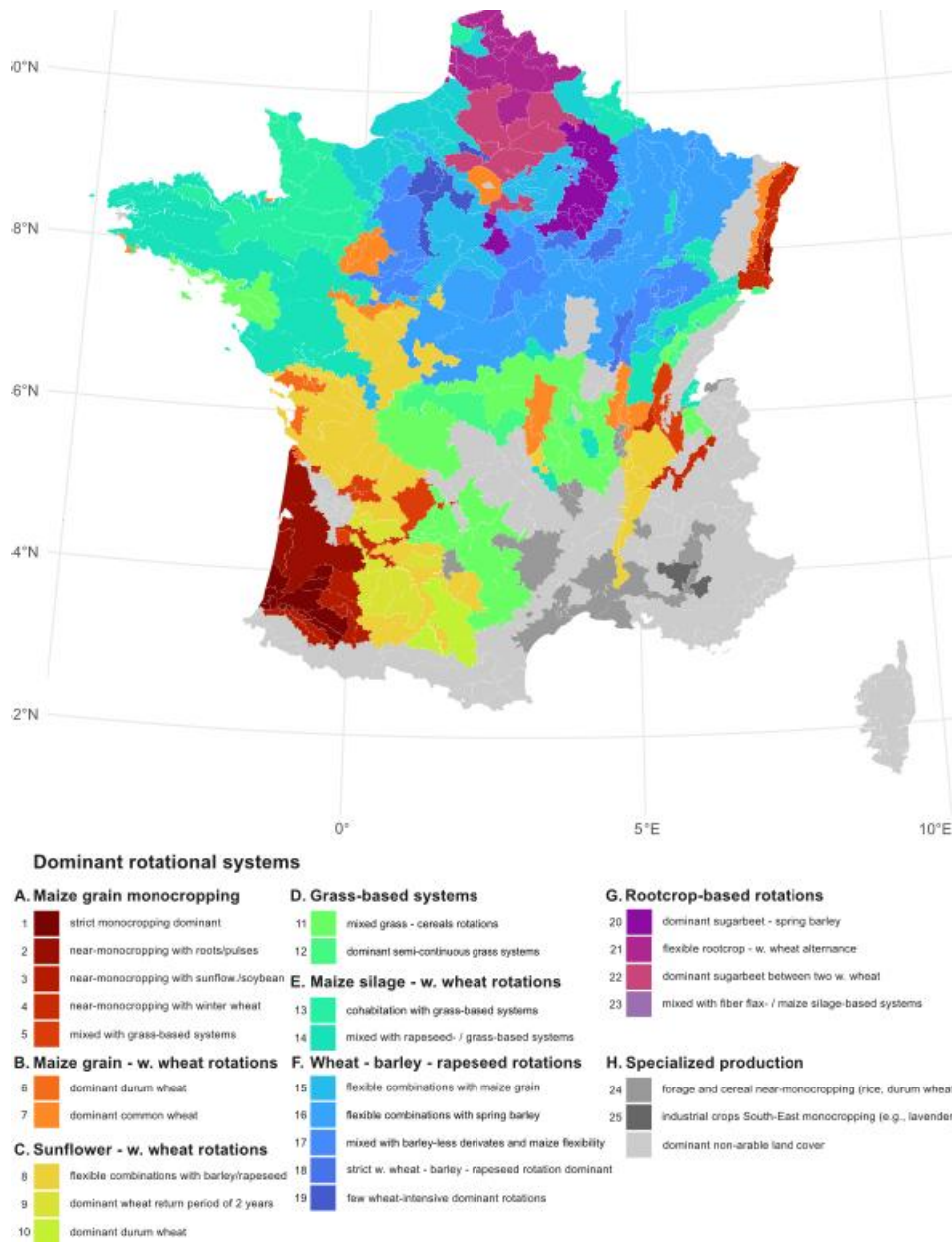
Clustering based on dominant rotation patterns grouped districts into 25 clusters, organized into eight broader groups (letters in **Figure 3**). Group A was defined by maize grain specialization, with clusters varying in the degree of strict versus near-monocropping (**Figure 4**), and in associated crops. For instance, Cluster 2 typically involved 2-3 years of consecutive maize grain followed by horticulture, pulses or potatoes (covering ~10% of arable land; **Table 2**). In Cluster 5, typical break crops rather included winter wheat and temporary grassland, and diverse locally specific rotations such as pulses (x3) followed by sunflower were observed. This highlights how districts can also be characterized by *typical* rotational practices beyond the dominating patterns. Cluster 1 exhibited the highest levels of strict maize grain monocropping and the lowest temporal crop diversity nationally (**Figure 2, Table 2**). Group B included Clusters 6 and 7, characterized by the two-year maize grain – winter wheat rotations and their derivatives. Cluster 6 showed strong correlations with winter and spring durum wheat, respectively covering 10% and 1.3% of agricultural area on average, approximately 100 times more than in other districts. Durum wheat was also prevalent in Cluster 10 (16% of agricultural area), where it typically rotated with sunflower in a two-year rotation (~20% of arable land). Cluster 10, along with Clusters 8 and 9, featured dominant sunflower – winter wheat rotations (Group C).

Group D encompassed districts with extensive permanent grasslands (covering 55-70% of total agricultural area), with arable land dominated by semi-continuous grasslands systems. Typical rotations included 2-3 years of temporary grassland, often with legume leys, maize silage, barley, or triticale. The high share of grass explained the low crop diversity and short rotation lengths observed (**Figure 2; Table 2**). Group E also included permanent and semi-continuous grasslands systems but was distinguished by prevalent two-year maize silage – winter wheat rotations and their derivatives. Maize silage near-monocropping was notably frequent in Cluster 13 (~10% on average), while Cluster 14 showed higher rotational diversity, with cereal-oilseed rotations (e.g., *w-b-r* and derivatives) alongside temporary grass – cereal – maize silage rotations. Group F, the largest (28.1% of national arable land), was centered around the *w-b-r* rotations and their derivatives. Clusters differed mainly in the weight of winter wheat and the integration of flexible crops integrated into the baseline *w-b-r* scheme. For instance, Cluster 19 exhibited the lowest crop diversity in the group (**Table 2**), with three dominant rotations (*w-b-r*, *w-w-b-r* and *w-w-r*) covering over 40% of arable land (**Figure 4**). Conversely, Cluster 16 -the largest in the group- showed the highest diversity, notably combining spring barley within *w-b-r* derivatives.

Group G consisted of districts dominated by root crop-based rotations in northern France (**Figure 3**). Clusters varied in the type of root crops and associated crops. Cluster 22 featured sugar beet – winter wheat alternance, while Cluster 20 involved typical four-year rotations with sugar beet and spring barley and exhibited one of the highest crop diversity levels (**Figure 2; Table 2**). Cluster 21 was associated with potato production, with typical alternation of sugar beet and potato every other year

418 with winter wheat (**Figure 4**). Rotations combining wheat, root crops, horticulture (~5% of agricultural
 419 area), and pulses were also common, contributing to some of the highest crop category diversities
 420 nationally. Cluster 23 was marked by four-year rotations involving flax and winter wheat along with
 421 maize silage, barley, potato or sugar beet. The prevalence of such flax-based rotational systems made
 422 the *Pays de Caux* district stand out with some of the longest rotation lengths and highest crop category
 423 diversity (**Figure 2**). Group H included southeastern France districts with near-monocropping of
 424 regional crops such as rice, sainfoin, and durum wheat (Cluster 24), as well as highly specialized
 425 systems like lavender monocropping (Cluster 25). These districts also had the highest levels of
 426 continuous organic farming (~10% of agricultural area). Further details on the rotational systems per
 427 cluster are provided in the **SM**.

428 **Figure 3: Clustering French agricultural districts by typical crop rotational systems**

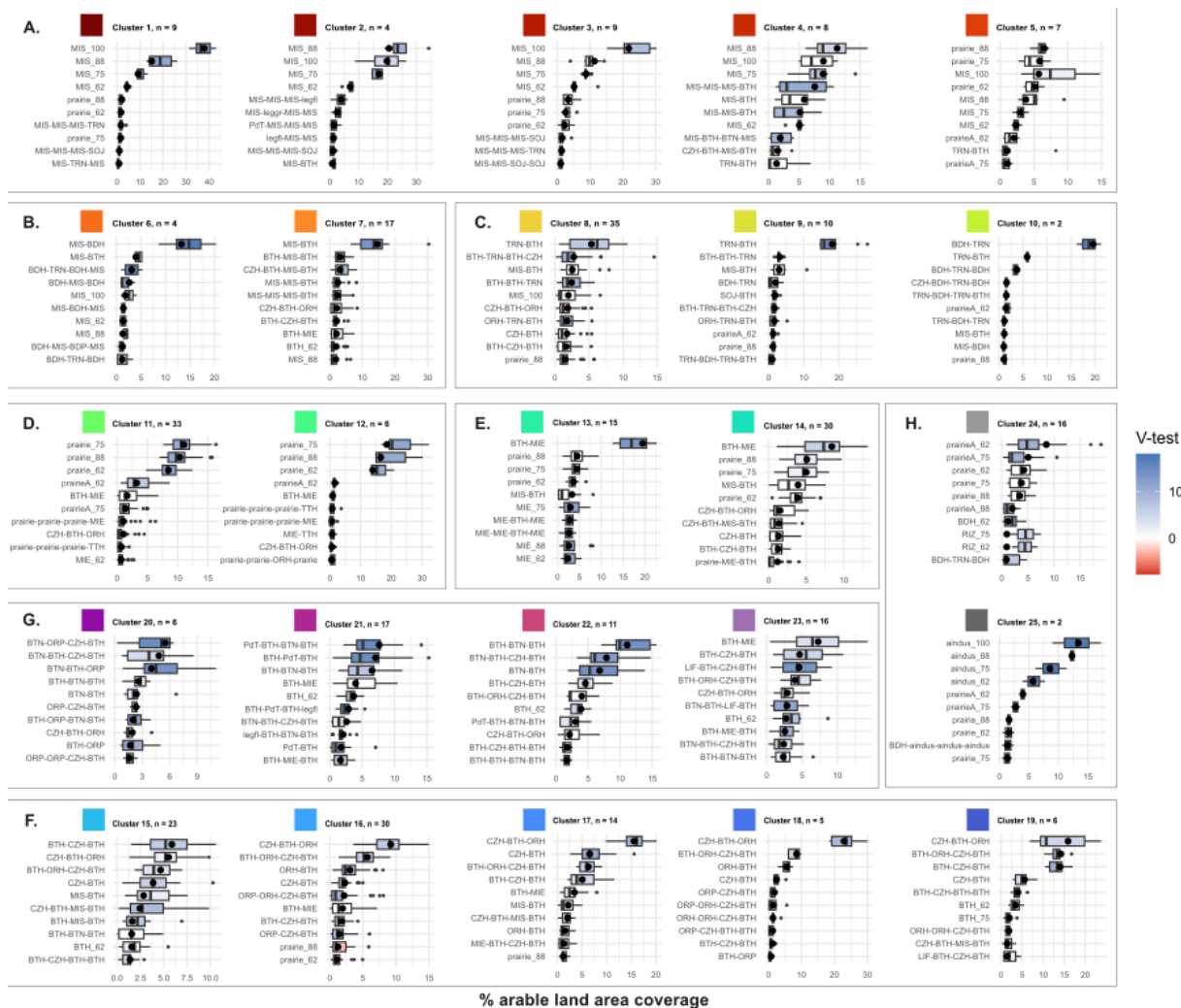


429

430 Quantitative data and description are provided in **Table 2** and **Figure 4**. w.: winter.

431

432 **Figure 4: Distribution of dominant crop rotations for 25 clusters of the French agricultural districts**



433
 434 Top-ten rotations per cluster. Boxplots show the intra-cluster inter-districts variability while black dots show the area-
 435 weighted mean at the cluster level (here, n represents the number of agricultural districts in a cluster). Blue tones indicate
 436 that a rotation is significantly representative of the cluster (higher intra-cluster average compared to total districts average)
 437 while red tones indicate that a rotation is significantly underrepresented in this cluster (see Section 2.2.3.). Colored squares,
 438 cluster numbers, and group letters, correspond to the legend used in Figure 3. Crop codes are described in Table 1.
 439 **Supporting data** is provided in Javourez, (2025).

440

Table 2: Key indicators for the 25 typical French rotational systems

n°	Cluster name	Area (%tot)	District count	Top-10 rotations (%area)	Rotation length <i>n</i>	%seq	<i>inv sim</i>	<i>inv sim cat</i>	Typical districts
1	Dominant maize grain strict monocropping	1.0%	9	76%	1.50	87%	1.58 (0.10)	1.48 (0.07)	<i>Pays de Gosse</i>
2	Dominant maize grain near-monocropping with roots and pulses	0.6%	4	76%	1.74	83%	1.74 (0.09)	1.68 (0.08)	<i>Landes du Médoc ; Hardt</i>
3	Dominant maize grain near-monocropping with sunflower and soybean	1.0%	9	59%	1.90	82%	2.03 (0.20)	1.79 (0.17)	<i>Bas Armagnac</i>
4	Dominant maize grain near-monocropping with winter wheat	1.3%	8	57%	2.47	80%	2.30 (0.20)	2.03 (0.13)	<i>Coteaux en bordure des Dombes ; Vallée de la Garonne</i>
5	Cohabitation of maize grain near-monocropping with perennial and grasslands	0.4%	7	36%	2.27	78%	2.42 (0.17)	1.95 (0.11)	<i>Vallée de la Dordogne</i>
6	Dominant maize grain – durum wheat rotations	0.5%	4	31%	2.90	76%	3.01 (0.08)	2.28 (0.11)	<i>Marais Poitevin</i>
7	Dominant maize grain – winter wheat rotations	2.5%	17	36%	2.83	78%	2.71 (0.18)	2.17 (0.12)	<i>Vallée de la Sarthe</i>
8	Flexible sunflower – winter wheat rotations with barley and rapeseed flexibility	11.2%	35	24%	2.95	75%	3.07 (0.17)	2.22 (0.10)	<i>Bergeacois ; Saintonge agricole</i>
9	Dominant sunflower – winter wheat rotations	2.9%	10	35%	2.86	76%	3.09 (0.15)	2.39 (0.08)	<i>Coteaux Sud Garonne</i>
10	Dominant sunflower – durum wheat rotations	1.6%	2	38%	2.84	76%	3.15 (0.13)	2.29 (0.02)	<i>Lauragais</i>
11	Mixed grass-cereal rotational systems	5.9%	33	40%	2.53	75%	2.51 (0.21)	2.09 (0.09)	<i>Monts du Jarez ; Segala</i>
12	Dominant semi-continuous grassland systems	0.9%	6	55%	2.05	75%	2.16 (0.25)	1.91 (0.15)	<i>Plateaux moyens du Jura</i>
13	Cohabitation of dominant maize silage rotational systems with grasslands	6.3%	15	49%	2.62	79%	2.55 (0.26)	2.09 (0.09)	<i>Région de Fougères ; Avranchin</i>
14	Mixed winter wheat – maize silage with rapeseed and grass-based rotations	12.1%	30	33%	2.85	76%	2.85 (0.22)	2.22 (0.11)	<i>Bocage ; Plaine du Forez</i>
15	Flexible winter wheat – rapeseed – barley rotational systems with maize grain flexibility	6.4%	23	31%	3.23	75%	3.19 (0.15)	2.17 (0.17)	<i>Vallées de la Marne et du Morin ; Brie humide</i>
16	Mixed winter wheat – rapeseed – barley rotational systems	13.7%	30	30%	3.22	74%	3.36 (0.19)	2.03 (0.12)	<i>Barrois vallée ; Plateaux de Bourgogne</i>

with spring barley flexibility									
17	Flexible winter wheat – barley – rapeseed rotational systems	5.7%	14	45%	3.12	78%	3.11 (0.19)	2.10 (0.11)	<i>Plaine Grayloise; Pays Sancerrois</i>
18	Specialized winter wheat – barley – rapeseed rotations	0.8%	5	48%	3.20	76%	3.43 (0.10)	1.93 (0.13)	<i>Pays d’Othe; Tonnerois</i>
19	Dominant winter wheat-based rotational systems	1.5%	6	64%	3.26	80%	2.89 (0.11)	2.02 (0.09)	<i>Plateau d’Evreux</i>
20	Sugar beet – spring barley rotational systems	4.6%	6	29%	3.44	73%	3.60 (0.15)	2.21 (0.20)	<i>Champagne Crayeuse</i>
21	Root crops – winter wheat rotational systems	4.7%	17	40%	3.31	75%	3.13 (0.19)	2.44 (0.11)	<i>Pays Aire; Ponthieu</i>
22	Sugar beet between winter wheats rotational systems	5.3%	11	47%	3.25	76%	3.02 (0.06)	2.29 (0.07)	<i>Noyonnais</i>
23	Diversified winter-wheat based rotational systems with flax, rapeseed, sugar beet and maize silage	4.9%	16	36%	3.22	75%	3.00 (0.15)	2.35 (0.17)	<i>Roumois; Plaine de Caen et de Falaise</i>
24	Specialized Southern-East France near-monocropping	1.6%	16	31%	2.73	73%	2.74 (0.19)	2.16 (0.19)	<i>Val de Durance ; Garrigues</i>
25	Specialized Southern-East France industrial crops	0.2%	2	53%	1.93	78%	2.22 (0.09)	1.94 (0.08)	<i>Plateau de Forcalquier</i>

442 Area (%tot): share of national arable land area by each cluster. Top-10 rotations (%area): share of arable land within the
443 cluster covered by the top 10 rotations (black dots in **Figure 4**). Other indicators were described in **Section 2.2.3**. For these,
444 area-weighted averages were calculated at the agricultural district level. Values represent intra-cluster means (standard
445 deviations) across districts. Cluster numbers correspond to those in **Figures 3** and **4**. A detailed description per district is
446 available in the **SM**.
447

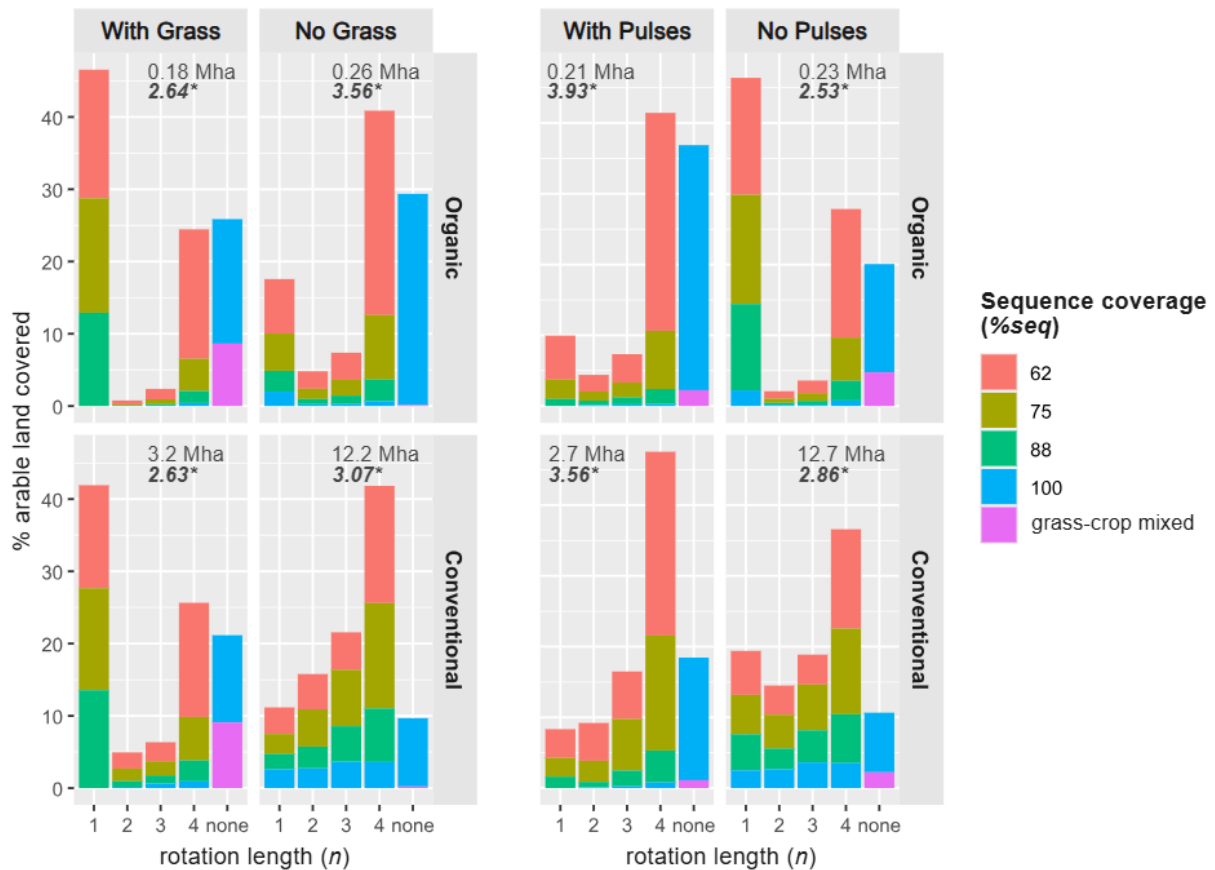
448 3.3. Organic farming shows greater crop diversity and flexibility in rotations

449 On land under continuous organic farming (0.44 Mha), crop rotation identification dropped to
450 ~76% nationally. Over one-quarter of organic arable land was occupied by semi-continuous grass- or
451 legume ley-based systems, contributing to the relatively short area-weighted rotation length observed
452 in organic systems (**Figure 5**). The most common organic rotations combined temporary grassland and
453 legume leys -at least two consecutive years- followed by cereals (~16,000 ha), or, occasionally maize
454 silage (~3,000 ha). Excluding grass and legume leys, the leading organic rotation was pulses – winter
455 wheat, though it covered only ~4,000 ha nationwide. Other typical organic rotations included soybean
456 – winter wheat, sunflower – winter wheat, and continuous horticulture (mostly vegetables), each
457 observed on ~2,000 ha.

458 Grass appeared at least once in 8-year sequences across 21% (~3.4 Mha) of total arable land, but across
459 41% of organic arable land. Interestingly, cropping systems involving grass showed no significant
460 difference in diversity or rotational structure between organic and conventional management. Semi-
461 continuous grasslands represented 1.2 Mha, mostly interrupted with maize silage (0.41 Mha), winter
462 wheat (0.33 Mha), or winter triticale (0.21 Mha). Grass was most often embedded in flexible four-year
463 rotations involving 2-3 years of temporary grassland followed by cereals, maize or legume leys., or in
464 non-classified sequences (**Figure 5**). The dominance of semi-continuous grasslands explains why

465 systems with grass showed lower crop-level diversity ($inv_sim = 2.63$) compared to those without
 466 (3.08), while exhibiting higher diversity at the category level (inv_sim_cat of 2.24 vs 2.15). Grass
 467 generally played a central role in rotations rather than being integrated as flexible crops into other
 468 systems. Nevertheless, it was occasionally found in semi-continuous legume leys and maize – winter
 469 wheat alternations (~65 kha each).

470 **Figure 5: Contrasted rotational features of cropping systems with grass or pulses**



471
 472 *: Inverse Simpson Index (inv_sim), area-weighted average per modality.
 473

474 In contrast, systems without grass showed clear differences between organic and conventional
 475 practices. In organic systems, strict -inflexible- rotations were nearly absent (~8,500 kha), and
 476 approximately 90% of arable land without grass exhibited at least two years of flexibility. Notably,
 477 nearly 30% lacked any identifiable rotational background (**Figure 5**). These organic grass-free systems
 478 had significantly higher diversity than their conventional counterparts (inv_sim : 3.56 vs. 3.07;
 479 inv_sim_cat : 2.40 vs. 2.14).

480 The greater length and flexibility of organic rotations were also linked to the widespread use of pulses,
 481 present on 50% of organic arable land but only 17% under conventional management (**Figure 5**). Pulses
 482 presence led to higher crop diversity (inv_sim : 3.59 vs 2.85; inv_sim_cat : 2.50 vs 2.09) for both organic
 483 and conventional systems. The observed lower diversity in organic pulse-less systems, relative to their
 484 conventional counterparts, is primarily attributed to the fact that ~50% of organic pulse-less surfaces
 485 consist of semi-continuous grasslands or legume leys, which are treated as near-monocropping in the
 486 diversity index used here. About 75% of organic areas with pulses were under flexible four-year
 487 rotations or more complex cropping systems, and ~35% of this area remained unclassified. Few
 488 individual organic rotations involving pulses exceeded 1,000 ha, reflecting high rotational variability.

489 The use of pulses as break crops in semi-continuous organic grassland and legume leys was the most
490 common. In conventional systems, they were mainly found as flexible crops in *w-b-r* rotations and
491 derivatives, winter wheat – maize or winter wheat – root crops alternations, and occasionally in near-
492 monocropping of maize grain or winter wheat. The most common pulse-centered conventional
493 rotations included: winter wheat – spring pea – winter wheat – rapeseed (~36,000 ha), winter wheat
494 – soybean (~24,000 ha), winter wheat (x2) – barley – spring pea (~19,000 ha and 14,000 ha,
495 respectively, for winter and spring barley), and winter wheat (x2) – spring pea (~14,000 ha).

496 3.4. Larger farms exhibit greater rotational diversity but lower spatial diversity

497 Across the 175,560 selected farms -covering approximately 89% (14 Mha) of total arable land-
498 larger farms exhibited more diverse and longer crop rotations on average (**Figure 6**). These farms also
499 tended to display higher temporal diversity, although the diversity at crop-category level (*inv_sim_cat*)
500 plateaued around 2.2 for farms with over 100 ha of agricultural area. Farms from size groups 100-200
501 ha and >200 ha accounted for 41% of the selected farms, but comprised 76% (10.6 Mha) of their arable
502 land. The greater number and diversity of crop rotations observed on larger farms can be attributed
503 to their broader crop portfolios: on average they cultivated 11-12 different crops over the eight years
504 (from the 41-crop-code nomenclature), compared to ~8 crops for 20-50 ha farms and ~5 for farms <20
505 ha (**Figure 6**). While more crops generally led to more rotation options, their average rotation length
506 was relatively similar, tending towards three years for larger farms. Rotation flexibility was also similar
507 across all farm sizes, averaging around two years variation within the eight-year period.

508 Yet, larger farms tended to have fewer distinct rotations and crops per unit area compared to smaller
509 farms (**Figure 6**). This indicates that, in larger farms, individual rotations -or crops- were observed over
510 larger surface areas, and crops were more often within the same rotations. This suggests a decline in
511 spatial crop diversity with increasing farm size. Nationally, the mean area occupied by a single rotation
512 was 3.1 ha in farms <20 ha (interquartile range: 1.5-3.8 ha), 6.7 ha in farms of 50-100 ha (IQR: 4.1-7.6
513 ha), and 13.7 ha in farms >200 ha (IQR: 8.5-16.1 ha).

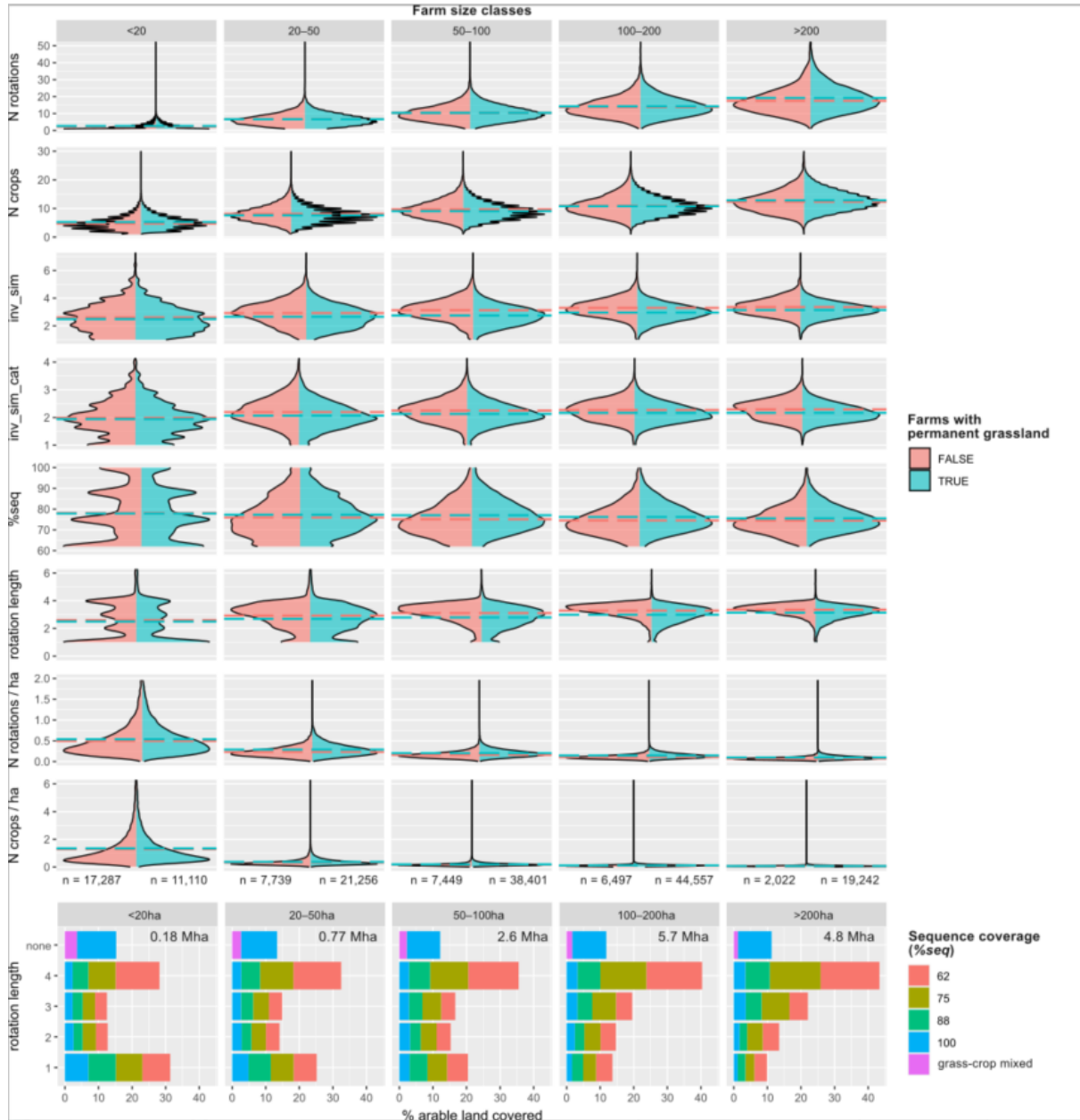
514 Small farms (<20 ha) displayed the most variable rotational patterns. Approximately 30% of their
515 arable land was under near-monocropping systems, while over 40% was managed with rotations of
516 four years (28%) or with no matching pattern (15%). In 67% of these small farms, a single crop rotation
517 accounted for half of their arable land, compared to just 15% and 6% for the 50-100 ha and >200 ha
518 farm groups, respectively. Despite this dominance of few individual rotations on small farms, no single
519 rotation was adopted by more than 10% of them, indicating a high overall diversity of cropping
520 systems. The most commonly implemented patterns among small farms were semi-continuous
521 grasslands and maize grain monocropping. Other rotations adopted by more than 1,000 farms in this
522 group included winter wheat alternated with either maize grain or sunflower. Notably, clusters
523 associated with maize grain monocropping (Group A, **Figure 3**) had the highest concentration of small
524 farms, representing up to ~40% of all farms for Cluster 1 (see **SM**).

525 Semi-continuous grassland emerged as the most widespread rotation type across all farm size groups.
526 Its prevalence largely explains the lower crop diversity and shorter average rotation lengths observed
527 on farms that included permanent grasslands in their agricultural area, compared to those without
528 (**Figure 6**). One third of farms with permanent grasslands also managed semi-continuous grasslands.
529 Although permanent grasslands covered only 5-25% of the agricultural area at the district level, they
530 were present on 77% of the 175,560 selected farms.

531 Beyond semi-continuous grasslands, the most widespread rotations across all farm sizes were winter
532 wheat – maize silage alternation (~16% of selected farms), the *w-b-r* and its derivatives (~14%), winter
533 wheat – maize grain alternation (~14%), and near-monocropping of winter wheat (~13%). In total, 28

534 distinct rotations were implemented by over 10,000 farms, and 223 rotations were found in more than
 535 1,000 farms. The *w-b-r* rotation, its derivatives, and winter wheat near-monocropping became
 536 increasingly dominant in farms larger than 100 ha. These rotations were present on over 60% of the
 537 farms in Group F districts, with dominant *w-b-r* rotational systems (**Figure 3**).

538 **Figure 6: Farm-level crop diversity and rotations indicators for French arable land**



539
 540 The farms selection procedure is described in the **Section 2.2.3**. Vertical ridgeline plots display the distribution of farm-level
 541 indicators within each farm size group, under two modalities (subpopulation shown; averages as dotted lines). *N rotations*:
 542 number of distinct crop rotations identified on a farm. *N crops*: number of unique crops cultivated over the eight years per
 543 farm (41 crop codes nomenclature in **Table 1**). Both indicators were also divided by the arable land area of the farm (/ ha).
 544 *inv_sim* and *inv_sim_cat* are indicators of temporal crop sequence diversity at two levels of crop aggregation (see **Section**
 545 **2.2.3**), calculated here as area-weighted averages at the farm level. *Rotation length* and sequence coverage (*%seq*) are also
 546 farm-level area-weighted indicators describing rotation characteristics. Stacked bar plots illustrate the composition of arable
 547 land in terms of rotation types, as in **Figure 5**, for each farm size group.

548

549 4. Discussions

550 4.1. Strength and limits of the flexible pattern-matching algorithm

551 The proposed field-level identification and classification procedure for flexible crop rotations
552 enables multi-scale and cross-thematic analysis of cropping and farming systems through the lens of
553 crop rotations. Our national-scale case study in mainland France demonstrates only a subset of the
554 analytical potential. Understanding the method's key features, adjustable parameters, and limitations
555 is essential before broadening its scope of application.

556 First, the procedure does not capture all rotation types and flexibilities. It targets dominant patterns,
557 simplifying inherently more complex annual cropping decisions. For instance, non-cyclical rotations, of
558 variable length, are not addressed. Moreover, "flexible rotation" was usually referring to the eventual
559 substitution of a crop by another within a baseline rotational scheme (Castellazzi et al., 2008), while
560 "flexible rotation" here referred to the sporadic introduction of crops between two occurrences of the
561 rotation. Accordingly, our approach can be seen as a groundwork for broader consideration and
562 characterization of flexibilities in rotations.

563 To achieve simplification, the selection process favors shorter rotations. Prioritizing longer matching
564 patterns was discarded as it led to over-selection of rotations with the maximum length ($n = n_{max}$),
565 which are more diverse hence individually less representative. Similarly, allowing identification of
566 patterns longer than $N/2$ (half the observed period) also resulted in selection towards longer, less
567 flexible, and less common rotations, as it required adjusting the sequence coverage threshold ($\%seq_{min}$)
568 depending on matching pattern length. Indeed, eight-year crop sequences would always match with a
569 five-year rotation, if still allowing three flexible years (corresponding to a $\%seq_{min}$ of 62% here).

570 The maximum rotation length (n_{max}) strongly influences the results, and was here capped at four due
571 to the eight-year observation window. For example, most rotations involving flax fibers were classified
572 as four-year rotations (mean length: 3.88 years, area-weighted). However, flax fibers were typically
573 observed once during this period (mean occurrence: 1.20, area-weighted), indicating a true return
574 period of six to seven years on the same field. Relying solely on the identified four-year rotation pattern
575 would therefore underestimate this return period. Since the method also retains flexibility
576 characteristics, these can be mobilized post-hoc to reconstruct longer, more representative flax fiber
577 rotations, suitable for application such as soil-crop modeling. Notably, rotations involving flax fibers
578 covered, on average, 72% of the eight-year period (area-weighted), implying the presence of at least
579 two flexible years. By identifying the most common flexible crops inserted into these rotations -using
580 study-area-level statistics- it becomes possible to reconstruct artificial but representative six-year
581 rotations that match the observed flax return period. This approach parallels the method used to
582 derive explicit rotations representative of near-monocropping practices (see **Section 2.1.4.**).

583 The approach was designed to identify steady-state rotations, not temporal changes or land cover
584 transitions. Longer time series, while improving confidence in rotation identification, might also
585 achieve lower overall identification rates as rotational systems shifting would gain more weight
586 (Debaeke et al., 2022; Mignolet et al., 2007). No specific treatment was implemented to identify
587 transition between arable land, permanent grasslands, perennial crop production, or other land cover.
588 For instance, a sequence such as A_A_A_grass_grass_grass_grass_grass was classified as semi-
589 continuous grassland (prairie_62), although it could indicate a transition from arable land to
590 permanent grassland. Identifying such grassland-to-cropland conversions would require context-
591 specific agronomic thresholds and co-variables (Xiao et al., 2015), which are beyond the scope of this
592 study. The decision to treat grass -and legume leys- as other crops shaped the interpretation of crop
593 diversity and rotation indicators. Approximately 7% of arable land was classified as semi-continuous

594 grassland (**Figure 1**) and treated as near-monocropping (one-year rotations). Consequently, indicators
595 for these areas were as low as those for monocropping systems such as maize grain. Agronomically-
596 informed diversity indicators would be better suited to reflect impacts of cropping systems on actual
597 biodiversity or other areas of protections, though such indicators would necessarily remain context-
598 specific (e.g., adapted to local pedoclimatic conditions; Keichinger et al., 2025). Here, diversity should
599 be interpreted in light of the chosen crop aggregation level, as a single crop code may obscure
600 underlying land cover diversity (Reumaux et al., 2023; van der Velde et al., 2024).

601 4.2. Appropriate scale of rotation analysis

602 This study also raises the question of the appropriate scale for crop rotation analysis. Nationally
603 dominant rotations were geographically associated with clusters of districts sharing similar production
604 orientations and high arable land coverage (e.g., France's 78 *w-b-r*-dominated districts; see **Table 2**),
605 but lacked representativeness elsewhere. The relevant scale may depend on the study's thematic focus
606 (e.g., watershed, administrative region), but our method imposes no strict lower spatial limit, as long
607 as representative near-monocropping practices can be reconstructed -typically requiring a minimum
608 of ~1,000 ha. Conversely, our method could help define what a relevant scale might be by identifying
609 shared rotation patterns from field-level data and using them to rezone agricultural districts
610 accordingly -making zoning an output rather than an input. While the farm-level results presented here
611 (**Section 3.4.**) were derived at national scale, different insights could emerge at intermediate (meso or
612 territorial) scales. Such scales may better capture trade-offs between farm structure (e.g., dominant
613 farm sizes), within-farm cropping and rotational systems, and the resulting inter-farms landscape-level
614 crop diversity, with both spatial and temporal patterns.

615 Future comparison of dominant rotations and their proportions using this method versus others (e.g.,
616 CropRota; Schönhart et al., 2011) or local expert knowledge could enhance interpretation. Such
617 comparisons may also guide the classification of the unmatched crop sequences, for example by
618 determining whether these reflect highly flexible or longer rotations not captured, independent annual
619 cropping decisions, or artifacts from shifting field boundaries over time, among other possibilities.
620 Annual updates from the LPIS dataset allow for routine monitoring of crop rotations and could be used
621 to test the robustness of the results across time periods (e.g., by excluding early years). A major
622 challenge, beyond parcel filiation through time, lies in the evolving LPIS crop code nomenclature -for
623 example, the post-2022 changes in the French LPIS.

624 4.3. From rotational analysis to impact assessment and policy design

625 Our method can be integrated into simulation-based assessment frameworks, as illustrated by
626 Launay et al., (2021), who used a crop model to evaluate the carbon footprint of French cropping
627 systems. However, it will require selecting which rotations to simulate over the investigated study area.
628 To extend simulation coverage, a similarity metric could be used to assign fields with un-simulated
629 rotations or unmatched patterns to the most similar rotation selected for simulation. Not mobilized
630 here, we explored such distance-based allocation by integrating custom Hamming distance metrics to
631 our method, with further details in the **SM**.

632 Improved knowledge of crop rotations enhances our ability to deeply characterize farming systems
633 (Mignolet et al., 2004). Identifying which crop rotations are implemented, and where, is essential for
634 designing, tracking, and evaluating agricultural policies, including the effectiveness of incentives or
635 interventions promoting sustainable practices. Our approach supports the characterization of baseline
636 rotations, monitoring their evolution at different temporal milestones. For instance, it could be used
637 to strengthen the role of crop rotations in future EU CAP frameworks by enabling quantitative
638 monitoring of rotational patterns, which are currently assessed mainly by crop frequency and

639 maximum consecutive occurrences (van der Velde et al., 2024). Quantifying and localizing crop
640 rotations also provide a grounded evidences for training, advisory services, and policy making across
641 thematic areas (e.g., organic farming, mixed crop-livestock systems) and spatial scales. For instance, it
642 can help disseminate how and under which conditions -currently minor- crops could be inserted into
643 existing cropping systems, and foster transition of practices. Such systematic rotational systems
644 innovation tracking is directly enabled by our approach, and entirely tunable by designing a crop code
645 nomenclature tailored to emphasize specific minor crops, as opposed to the dominant-crop oriented
646 nomenclature proposed here (**Table 1**). Other application examples include unravelling the relation
647 between rotational practices and intercrop management. Albeit necessary to assess carbon storage,
648 erosion, or water issues, French LPIS do not provide intercrop management data. Jointure with remote
649 sensing data may offer opportunities for this need.

650 Beyond identifying “which” and “where”, understanding “why” and “how” specific rotations are
651 adopted into different farming systems -e.g., if intentional or conjectural- remains crucial. Future
652 research should explore the drivers of rotational flexibility and the role of specific flexible crops,
653 potentially using decision-rule frameworks at the farm level to classify not only by observation but also
654 by farmer intent (Dury et al., 2013). Unraveling the drivers of rotation adoption can be achieved by
655 linking this rotation analysis to farming structure datasets covering e.g., livestock, yield, management
656 practices, pedoclimatic variables and market conditions (Burchfield et al., 2024; Chongtham et al.,
657 2017; Pott et al., 2023).

658 5. Conclusion

659 We proposed a novel generic pattern-matching algorithm to identify and classify crop rotations
660 from field-level annual crop sequences, enabling the quantitative assessment of rotations
661 characteristics, such as composition, length, and flexibility, across spatial scales. Applied to the 15.8
662 million hectares of arable land in mainland France from 2015 to 2022, our approach revealed that
663 national-level cropping systems are structured around a limited yet flexible and regionally distinct set
664 of crop rotations. A spatial typology at the agricultural district level identified 25 distinct zones with
665 typical rotational systems. At the national scale, organic farming systems exhibited greater crop
666 diversity and rotational flexibility than conventional systems. On average, larger farms implemented
667 longer and more diverse rotations than smaller farms, but over larger areas, resulting in lower spatial
668 diversity. The proposed method is adaptable to various regions and objectives, providing a robust tool
669 for the diagnosis and assessment of cropping and farming systems. It may equip agricultural
670 stakeholders at multiple levels with a mean to characterize these agricultural systems and better target
671 improvement strategies. It also lays the groundwork for large-scale simulations that accurately
672 represent field-level practices, while allowing localized focus on innovative or specific rotational
673 systems. Future research should integrate rotation-level data with farm management, biophysical, and
674 socioeconomic data to uncover the drivers of rotation adoption with their respective flexibilities, as
675 well as anticipating their evolution in a changing world.

676 6. Data statement

677 Supporting data is available at <https://doi.org/10.57745/XJ13KO>, and the code use to generate and
678 analyze the data for the case study is available at [https://forge.inrae.fr/ugo.javourez/crop-rotations-
679 pattern-matching-algorithm](https://forge.inrae.fr/ugo.javourez/crop-rotations-pattern-matching-algorithm).

680 7. CRediT author statement

681 **Javourez Ugo**: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data
682 curation, Writing – Original draft, Visualization. **Girault Baptiste**: Conceptualization, Methodology,
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684 Editing. **Dedieu Marie-Sophie**: Conceptualization, Resources, Writing – Review & Editing. **Therond**
685 **Olivier**: Conceptualization, Methodology, Writing – Review & Editing, Supervision, Funding acquisition

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692 9. References

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