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Impact of farmland fragmentation on rainfed crop allocation in Mediterranean landscapes: A case study of the Lebna watershed in Cap Bon, Tunisia

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Introduction

Agricultural landscapes provide ecosystem services and disservices that are driven by land use pattern dynamics resulting from crop spa- tiotemporal distribution (Millennium Ecosystem Assessment, 2005; IAASTD, 2008). Crop mosaics related to spatial patch arrangement and crop succession impact the sustainability of agricultural production (Jackson et al., 2007) as well as numerous biophysical processes such as water, erosion and contaminant fluxes (Joannon et al., 2006; Wohlfahrt

et al., 2010; Colin et al., 2012), biotic diversity (Joannon et al., 2008) and gene fluxes (Viaud et al., 2008). Therefore, characterizing the drivers of crop allocation to fields is a prerequisite for (1) exploring and

simulating spatially explicit plausible land use scenarios, and (2)

quantifying the subsequent ecosystem services and disservices (Benoît

et al., 2012; Rizzo et al., 2013).

As discussed in previous studies, land use pattern dynamics on agricultural landscapes result from crop allocation rules that are de-

fined at the farm scale and that drive both the successions of crops over

several years and the annual distributions of crops among farmlands

(Joannon et al., 2008; Thenail et al., 2009; Castellazzi et al., 2010; Houet et al., 2010; Sorel et al., 2010; Schaller et al., 2012; Stoebner and Lant, 2014). Once crops are selected for any year, allocation rules concern a choice (1) of suitable cultivation area for each crop (all sui- table plots for the considered crop), (2) of the crop surface area (total area of a considered crop on the farmland), (3) of crop return time (acceptable time to reseed the same crop on the same plot) and (4) of preceding-following crop pairs (acceptable temporal crop sequences) (Aubry et al., 1998). Describing these rules and identifying their drivers is necessary to explain the observed spatiotemporal patterns of crop location at the landscape scale (Schaller et al., 2012). This is also a prerequisite both to simulate landscape patterns and to compel land-scape evolution models (Thenail et al., 2009; Castellazzi et al., 2010; Houet et al., 2014; Jahel, 2016). As shown by most of the above-mentioned studies, the driving factors of crop allocation rules are in-ternal (e.g., farming system, characteristics of farm resources such as land or workforce) and/or external (e.g., market conditions, climate) on a farm. Intra-farmland fragmentation, hereafter called farmland fragmentation, is a typical characteristic of cultivated landscapes (Demetriou et al., 2013) that can be an internal driver of crop allocation. Farmland

fragmentation is defined as the intensity of the division of farmland into

numerous small fields that are spatially dispersed. Several processes can

explain farmland fragmentation, including field fragmentation and

farm area distribution. In southern Mediterranean countries, farmland

fragmentation has been favoured by privatization policies for collective lands (Ben Saad and Bourbouze et al., 2013), legal rules governing inheritance, urbanization and the

development of other land uses (Jouve, 2001). The average farm area is small, and the dispersion of

farm fields is very common in these countries. For instance, the records

from 2004 to 2005 indicate that 54% of Tunisian farms were smaller

than 5 ha, corresponding to 11% of the total agricultural area, 43% were between 5 and 50 ha, corresponding to 55% of the total agri- cultural area, and only 3% were larger than 50 ha, corresponding to

34% of the total agricultural area (MARH, 2006). In terms of farmland fragmentation, 69% of the Tunisian farms smaller than 5 ha had only

one field block, whereas 62% of the farms larger than 5 ha had two or

more field blocks, where a field block is defined as a group of fields less

than 500 m from each other.

Numerous studies have shown the impact of farmland fragmenta- tion on crop management and location, as well as the consequences on the economics and environment of the farm. For farmers, farmland fragmentation may generate opportunities related to risk management or crop scheduling (Bentley, 1990; Markussen et al., 2016). However, farmland fragmentation also generates management constraints, such

as (1) reduced efficiency of field machinery due to the small sizes and/ $\!\!\!$

or irregular shapes of the fields, or (2) excessive or differentiated

farmstead-field distances. These opportunities and constraints impact

crop locations and management at the farm scale (McCall, 1985; DeLisle, 1982; Deffontaines et al., 1995; Gonzalez et al., 2004; Morlon

and Trouche, 2005; Thenail et al., 2009; Markussen et al., 2016). Consequently, farmland fragmentation impacts the economic (Latruffe

and Piet, 2014; Gonzalez et al., 2004; Markussen et al., 2016) and en- vironmental (Sklenicka, 2016) performance of farms. Farmland frag- mentation also creates a context of geographical proximity, since each

field managed by a farmer is likely to be surrounded by several fields

that are managed by other farmers, which may generate neighbouring effects and interactions.

Neighbourhood interactions are a well-known driving factor of land use patterns (Verburg et al., 2004; Sidharthan and Bhat, 2014; Stoebner and Lant, 2014; Xiao et al., 2015; Anputhas et al., 2016) and correspond

to the first law of geography (Tobler, 1970). Neighbourhood interactions reflect attraction or repulsion effects between land use types. For

example, the high probability of a certain type of land use at a given place in the neighbourhood reflects an attraction effect. Attraction ef-

fects may be linked to (1) common driving factors such as soil type, microclimatic conditions, and land tenure arrangement, or (2) spatial

processes that generate agglomeration benefits, such as learning

through imitation and/or positive spillovers (Xiao et al., 2015;

Anputhas et al., 2016; Sidharthan and Bhat, 2014; Stoebner and Lant,

2014). Repulsion effects may result from different needs in terms of

biophysical conditions (e.g., soil/crops adequacy) or from damage

caused by a land use type (e.g., damage to crops by rabbits,

boars and birds from nearby forests). These neighbouring effects are commonly quantified in land use models based on grid data that refer to neigh-

bouring pixels (Verburg et al., 2004). To the best of our knowledge, these effects are rarely quantified in models that consider the farm

scale, and, if so, they refer to the centroids of neighbouring farms

(Martinetti and Geniaux, 2016) and not the neighbouring fields.

Overall, existing studies have not addressed the impact of farmland

fragmentation and the subsequent neighbouring interactions on crop allocation rules, whereas crop management is likely to be strongly driven by a combination of the two factors. Therefore, the current study aimed to explore how much farmland

fragmentation can drive the de- cisions made by farmers about annual crop allocation by characterizing

and quantifying the influences of both crop sequences and neigh-

bouring crops at the field scale. We addressed this issue by considering

an agricultural watershed located within the Cap Bon Peninsula in

northeastern Tunisia.

2. Materials and methods

2.1. Study area

The study area was the Lebna watershed (210 km^2 ,

36°43'N-36°53'N; 10°40'E-10°58'E) located in the Nabeul Governorate on the Cap Bon Peninsula in northeastern Tunisia (Fig. 1). The Lebna landscape includes three zones (upstream, intermediate and down- stream) according to geomorphologic, geological and land cover-land use criteria (IAO, 2002). A continuous ecosystem gradient is observed along the upstreamdownstream transect. The upstream part, ranging from 200 m a.s.l. to 637 m a.s.l., corresponds to the most abrupt gra- dient of the watershed. The intermediate zone, with altitudes ranging from 80 m a.s.l. to 200 m a.s.l., corresponds to the Lebna hills and in-cludes a network of wadis (i.e., intermittent rivers). The downstream zone, with altitudes ranging from 0 m a.s.l. to 80 m a.s.l., includes the Lebna plain. The climate regime is at the boundary between subhumid and semiarid (IAO, 2002). From downstream to upstream, the mean annual rainfall and the mean annual evapotranspiration (Penman- Monteith reference crop) range from 450 mm to 800 mm and from 1000 to 1500 mm, respectively (IAO, 2002; Zitouna-Chebbi et al., 2012). The Lebna watershed is subject to soil erosion and subsequent reservoir

siltation (IAO, 2002; Gaubi et al., 2016). The diffuse erosion rate, which

results from agricultural practices, is four times greater than the con-

centrated erosion rate (Ben Slimane et al., 2013, 2016). One-third of the watershed area is covered by natural vegetation (Table 1). The natural vegetation areas include the steepest parts of the watershed, as well as the shores of the hill reservoirs, lakes and wadis. Arable lands are spread across 57% of the watershed area. Agricultural systems are mainly based on rainfed mixed farming and livestock. As in other rainfed agricultural systems in North Africa (Latiri et al., 2010), the Lebna agriculture mainly includes cereal production, although its climate increases the crop diversity. Annual crops areas spread over 49% of the watershed area. The annual crops include grain cereals (mainly wheat), fodder crops (mainly barley, oats and triticale), spices (mainly coriander) and legumes (mainly fava bean). Perennial crops (mainly olive trees) cover 8% of the total area of the watershed. Livestock



Fig. 1. The study area (Lebna watershed). The map was obtained from manual digitization and classification of a Spot 6 image dated 03/21/2016 and a Google Earth image dated 05/24/2016.

Table 1

Cover of land use types and land use classes within the Lebna watershed. Percentages are given relative to the total watershed area.

Land use type	Land use class	Cover (%)
Natural and semi-natural areas	Forests, shrubs, herbaceous pastures, outcrops of sandstone	34
	Artificial lakes, dam, sebkhas, wadis	6
Sealed manmade areas	Roads, dirt tracks, isolated houses, urban areas	3
Rainfed mixed farming	Annual crops	49
	Perennial crops	8

husbandry includes cattle, sheep and goat breeding. Livestock feeding relies on farm production, natural vegetation, and external food supplements. There are three main forms of grazing: (1) grazing of fodder crops, (2) grazing of crop residues, and (3) grazing of natural vegetation. Animals can either be tethered to a stake or can graze freely under shepherd supervision.

Within the Lebna watershed, the cultivated landscape consists of a mosaic of very small agricultural fields, and the average field area is less than 1 ha. The Lebna watershed is a landscape of open fields; most fields are unfenced and cannot be directly accessed by roads. Due to the small farm sizes, most farmers have little equipment and therefore outsource mechanized operations to agricultural contractors. The crop cycles range from autumn to summer (Fig. 2), and crop scheduling differs from one crop to another (Mekki et al., 2006). Cereals may be stereotypically rotated with legumes or spices to capture the benefits of nitrogen fixation (in the case of legumes) and/or to break pest or weed cycles.

2.2. Overview of the methodological strategy

To evaluate any possible influence of farmland fragmentation on the decisions by farmers on annual crop allocation, we conducted a comparative analysis between isolated and non-isolated fields belonging to a sample of farms. Isolation/non-isolation was related to the spatial distribution of the fields belonging to a given farmer. A field was defined as an agricultural plot managed by a single farmer and with a single annual crop.

As shown in Fig. 3, the methodological strategy included three steps. The data collection (Step 1) occurred during two successive an-

nual crop cycles (2014–2015 and 2015–2016) within the fields of the selected farmers and within their neighbourhoods. After splitting the sample of the surveyed farmer fields (FFs) between isolated and non-isolated fields (Step 2), we used a two-stage procedure to compare the

crop allocation rules used in each of the two subsamples (Step 3). First, we characterized the influences of crop sequences and neighbouring crops on the annual crop allocation. Second, we quantified the statistical significances of the relative influences of both crop sequences and neighbouring crops.

2.3. Geo-database of surveyed agricultural fields

To characterize and quantify the influence of crop sequences on crop allocation, we conducted field surveys over two successive crop cycles (2014–2015 and 2015–2016) on 30 farms. The farms were selected to account for a diversity of size, level of farmland fragmentation and geographical location (spatial diversity of relief, soil and climate). The selected farms included 360 fields in 2014–2015 and 355 fields in 2015–2016 because of a common process of field aggregation/splitting from one year to another. These fields are hereafter called farmer fields (FFs). The field survey included the type of crop sown on the fields during the 2014–2015 and 2015–2016 crop cycles. We differentiated three main crop types according to their main agronomic characteristics and use: (1) wheat (always harvested as a cereal grain); (2) spice/legume crops (mainly used for human food, stereotypically rotated with wheat); and (3) fodder crops.

To characterize and quantify the influence of neighbouring crops on crop allocation, we conducted a complementary land use survey in the neighbourhoods of the FFs during the 2015–2016 crop cycle. This survey recorded the type of crop sown on 1220 fields distributed between the fields that were adjacent to the FFs, and some non-adjacent fields in the vicinity that were sown with annual crops (Fig. 4). The farmers of these fields were unknown. The land use survey in the neighbourhood of the FFs also included the perennial crops and the



FFCrop 2015-2016 = f_1 (FFCrop 2014-2015) FFCrop 2015-2016 = f_2 (NFCrop 2015-2016) FFCrop 2015-2016 = f_3 (FFCrop 2014-2015, NFCrop 2015-2016) FFCrop 2015-2016 = f_3 (FFCrop 2014-2015, NFCrop 2015-2016)

Fig. 3. Methodological framework. Step 1 was described with a Unified Modelling Language (UML) class diagram.

natural or manmade elements of the land adjacent to the FFs. We accounted for the primary adjacent roads and dirt tracks that were wide enough to act as a barrier.

All of the FFs as well as the farmsteads were precisely geo-referenced and mapped (Fig. 4) using a two-step procedure. The field boundaries were first geolocalized using Global Positioning System (GPS) routes (precision ≤ 5 m). Second, the limits were redrawn using both a panchromatic Spot 6 image (precision 1.5 m) dated 05/03/2015 for the 2014–2015 crop cycle and a panchromatic Spot 6 image (precision 1.5 m) dated 03/21/2016 for the 2015–2016 crop cycle. The other field boundaries were digitized from the panchromatic Spot 6 image dated 03/21/2016.

2.4. Data analysis

2.4.1. Splitting the dataset into isolated and non-isolated fields We assumed that for any FF, the annual crop allocation was driven by both (1) the relative importance of neighbouring fields outside the farm and (2) the farmstead-field distance. Non-isolated fields were defined as the fields located in a block of fields belonging to the same farm, with the nearest boundary of the block less than 300 m from the farmstead. Isolated fields were defined as fields that were (1) mainly surrounded by fields belonging to other farms, and (2) whose distance to the farmstead was greater than 300 m.

As seen in Figs. 3 and 4, two typical farmland structures were observed: (1) aggregated farmlands with fields mostly grouped around farmsteads, and (2) highly fragmented farmlands, including dispersed individual fields or small field islets. Beyond these main trends, we had to proceed with few field farms that depicted different characteristics. At the watershed extent, we observed that 4% of the fields were located in large blocks far from the farmstead, which were classified as isolated or non-isolated fields according to the accessibility of the field from the road. We also observed that 3% of the fields were located less than 300 m from the farmstead, and these fields were classified as isolated



Fig. 4. Location of the fields surveyed in the 2015–2016 crop cycle within the Lebna watershed and two typical farmlands (FL1 and FL2). FL1 is an aggregated farmland and FL2 is a scattered farmland.

fields because they were not visible from the farmstead and their neighbours were mainly fields that did not belong to the same farmer.

2.4.2. Characterizing the influences of crop sequences and neighbouring crops on crop allocation

The influences of crop sequences and neighbouring crops were characterized for each of the two FF subsamples (isolated and nonisolated fields).

We assessed the influence of the preceding crop on the current crop by performing a Pearson chi-square test on a contingency table that crossed the crop types of the previous (2014–2015) and current (2015–2016) crop cycles. Since the field limits could be mismatched from one year to another because of field aggregation/splitting, we registered the preceding crop for a given field in 2015–2016 as the crop that dominantly covered the corresponding area in 2014-2015.

We next analysed the influence of neighbouring crops on the current crop in a given FF using the data collected for 2015–2016 and two complementary neighbourhood metrics. We successively considered neighbourhood as (1) a binary property when two fields share a boundary (adjacent neighbours), and (2) a continuous distance between field centroids.

For the binary neighbourhood metric, the influence of the neighbourhood on crop i in the FFs (with i being [wheat, spices/legumes, fodder crops]) was explored as follows: we successively calculated the fraction y of the FFs with crop i having at least x% of adjacent neighbours with the same crop i, and we constructed the resulting distribution curves fy = f(x) for x, ranging from 5 to 100, at a 2.5 step.

For continuous neighbourhood metric, the influence of neighbourhood on a crop i was explored as a function of the distance h between fields centroids (including adjacent neighbours but not only) using a spatial indicator correlogram (Webster and Oliver, 2001) as expressed in Eq. (1). The correlogram was computed here from all field pairs including at least one of the FFs, as follows:

$$\rho_i(h) = \frac{1}{n_h} \frac{\sum_{(s_a, s_\beta) \mid s_a \in i} (1 - \bar{i}) (1_i(s_\beta) - \bar{i})}{var(1_i(s))}$$
(1)

where ρ_i (h) denotes the spatial autocorrelation for crop i at the lag distance h expressed in metres; S_{α} and S_{β} are two fields where S_{α} is cropped with i and the (S_{α}, S_{β}) distance equals h; n_h denotes the total number of field pairs at distance lag h; *t* denotes the overall proportion of crop *i*; $\mathbb{I}_i(s_{\beta}) = 1$ if S_{β} is cropped with i and is zero otherwise; s denotes any parcel in the population; and $\mathbb{I}_i(s) = 1$ if *S* is cropped with i and is zero otherwise.

For both metrics, we tested the significance of the results by comparing them to a spatially random distribution of neighbouring crops. For that purpose, spatial Mantel tests (Legendre, 2000) consisting of crop value permutations on neighbouring fields in respect to the overall crop distributions and field locations (Fig. 5) were performed. The 95 and 99% confidence bands of the Mantel test were built in both cases from 1000 permutations.

2.4.3. Quantifying the relative influences of crop sequences and neighbouring crops on crop allocation

Linear discriminant analysis was applied independently to the isolated and the non-isolated fields, which allowed for the quantification of the respective weights of the "preceding crop" and three variables describing the adjacent crops on the crop allocation in the fields. These three variables were the fractions (relative to all adjacent neighbours) of wheat fields, spice/legume fields and fodder fields.

Three prediction models were developed from the preceding crop variable, the adjacent crop variables, and the entire set of variables. The models were calibrated over a stratified field subset, including twothirds of the total sample of isolated or non-isolated FFs, with a random selection that represented the observed fractions of the crop types over the entire sample. Then, for each model, the overall accuracy was computed over a validation subsample that included the remaining fields. The procedure was repeated 1000 times, and the results were



Fig. 5. The observed and randomly permutated crops around wheat field Pi in a zoom area with 29 fields. The number of fields for a given crop type is constant for the observed distribution and the two random distributions. In the observed distribution, the neighbouring wheat fields represented 83% of the land use pieces adjacent to Pi; but they represented only 33% in both random permutations a and b.

averaged. Finally, the prediction rate of each model was compared to the prediction obtained from 1000 random crop distributions. We used Student's t-tests to assess the significances of the observed differences in the prediction rates.

2015–2016 crop cycle (Table 2). On average, annual crops represented 92% of the total cultivated area and were almost equally distributed among the three types of crop. The remaining area included orchards (7% of the cultivable area) and fallow (1%). No relationship was observed at the farm scale between the total cultivable area and the distribution of crops.

3. Results

3.1. Diversity of crops and farmland characteristics in the surveyed farms

The cultivated area per farm ranged from 0.9 to 28.2 ha during the

A seen in Table 3, in 2015–2016, 239 FFs were considered isolated, and 116 were non-isolated. 12 farms were considered totally or partially aggregated with few isolated fields, and 18 were considered nonaggregated with several isolated fields. On average, isolated fields were

Table 2 Distribution of crops in the surveyed farms for the 2015–2016 crop cycle.

Farmer	Cultivable area (ha)	ha) % of the cultivable area								
		Annual cr	rops	Others						
		Wheat	Spices and legumes	Fodder crops	Total annual crops	Arbori-culture	Fallow	Total other		
E01	7.5	32	30	26	87	13	0	13		
E02	26.6	20	13	55	89	11	0	11		
E13	1.4	37	61	0	98	2	0	2		
E25	15.0	57	17	25	100	0	0	0		
E28	17.1	0	21	78	99	0	1	1		
E03	22.4	35	29	34	99	1	0	1		
E04	3.4	0	35	53	88	0	12	12		
E05	9.4	37	46	16	98	0	2	2		
E07	28.2	40	15	45	100	0	0	0		
E10	18.3	9	18	14	41	41	18	59		
E14	18.4	11	19	64	94	6	0	6		
E15	12.5	60	37	0	97	3	0	3		
E06	2.5	54	32	13	100	0	0	0		
E08	11.8	22	28	34	84	16	0	16		
E09	10.2	37	35	8	80	20	0	20		
E11	5.3	38	28	33	100	0	0	0		
E12	18.6	36	29	29	94	4	2	6		
E16	13.1	43	46	10	100	0	0	0		
E17	7.6	0	17	36	54	46	0	46		
E18	11.7	19	12	66	97	0	3	3		
E19	2.1	38	0	44	82	18	0	18		
E20	22.9	53	36	12	100	0	0	0		
E21	17.5	19	69	12	100	0	0	0		
E22	0.9	47	0	53	100	0	0	0		
E23	1.8	78	0	22	100	0	0	0		
E24	4.4	17	60	23	100	0	0	0		
E26	4.3	62	38	0	100	0	0	0		
E27	2.8	0	100	0	100	0	0	0		
E29	2.4	31	64	5	100	0	0	0		
E30	21.8	39	40	18	96	4	0	4		
Whole sample	342.0	31	30	31	92	7	1	8		

Table 3										
Distribution of isolated and	non-isolated annual of	crop	fields	on	the	surveyed farms	for the	he	2015-2016 crop	cycle

Farmer	Type of farmland	Isolated fields			Total isolated area	Non-isola	ated fields	Total aggregated area	
		Number	Mean area (ha)	Mean FFD (km)	(na)	Number	Mean area (ha)	Mean FFD (km)	(na)
E01	aggregated	0	_	_	0	9	0.7	0.1	6.5
E02	aggregated	0	-	-	0	35	0.7	0.3	23.5
E13	aggregated	0	-	_	0	4	0.3	0.1	1.3
E25	aggregated	0	-	_	0	16	0.9	0.3	15.0
E28	aggregated	0	-	_	0	5	3.4	0.5	16.8
E03	partially aggregated	1	1.2	2.1	1.2	14	1.5	0.3	20.9
E04	partially aggregated	1	0.6	1	0.6	5	0.5	0.2	2.4
E05	partially aggregated	2	1.8	0.8	3.6	5	1.1	0.2	5.7
E07	partially aggregated	4	1.4	1.5	5.5	6	3.8	0.2	22.7
E10	partially aggregated	4	0.8	0.5	3.1	5	0.9	0.4	4.3
E14	partially aggregated	5	0.9	1.3	4.7	7	1.8	0.4	12.5
E15	partially aggregated	4	1.3	1	5.0	5	1.4	0.9	7.1
E06	scattered	6	0.4	0.3	2.5	0	_	-	0
E08	scattered	21	0.5	2.3	9.9	0	_	-	0
E09	scattered	15	0.5	1	8.2	0	_	-	0
E11	scattered	8	0.7	1	5.3	0	-	-	0
E12	scattered	24	0.7	0.8	17.6	0	-	-	0
E16	scattered	21	0.6	1.2	13.0	0	-	-	0
E17	scattered	10	0.4	2.3	4.1	0	-	-	0
E18	scattered	11	1	1.2	11.4	0	-	-	0
E19	scattered	6	0.3	1.3	1.7	0	-	-	0
E20	scattered	9	2.5	1.6	22.9	0	-	-	0
E21	scattered	14	1.6	0.8	17.5	0	_	-	0
E22	scattered	3	0.3	0.6	0.9	0	-	-	0
E23	scattered	3	0.6	1.5	1.8	0	-	-	0
E24	scattered	7	0.6	1.1	4.4	0	-	-	0
E26	scattered	5	0.9	1.2	4.2	0	-	-	0
E27	scattered	2	1.4	1.5	2.8	0	_	-	0
E29	scattered	15	0.2	0.9	2.4	0	-	-	0
E30	scattered	38	0.6	1.1	21.0	0	-	-	0
Whole sample		239	0.7	1.2	175.5	116	1.2	0.3	138.8

Note: FFD is the farmstead-field distance.

characterized by a smaller area (0.73 ha) and a larger farmstead-field distance (1210 m) than non-isolated fields (1.2 ha, 320 m).

3.2. Effect of the preceding crop on crop distribution

The results of the distribution of crops in a FF in accordance with the preceding crop are depicted in Fig. 6. The figure shows that regardless of field context (i.e., isolated or non-isolated), wheat as a preceding crop was positively associated with spices/legumes as a following crop, and vice versa. Fodder crops were positively associated with fodder crops. In the case of isolated fields, both "wheat-wheat" and "spices/legumes – spices/legumes" pairs were significantly underrepresented.

3.3. Effect of neighbouring crops on crop distribution

Fig. 7 presents the distribution curves of each crop type on the FFs according to the occurrence of the same crop type in the adjacent neighbourhoods (binary neighbourhood metric exploration). For any crop i, a distribution curve above the 95–99% confident bands indicates that this crop is significantly more surrounded by the same crop than by other crops (attraction effect). Conversely, a distribution curve under the 95–99% confident bands indicates a repulsion effect. A distribution curve within the confidence band indicates that the distribution of crop i does not depend upon the adjacency of the same crop. Consequently, Fig. 7 clearly shows significant differences between isolated and non-isolated fields. In isolated fields, wheat was surrounded much more by wheat than by other crops. Similarly, spice/legume crops were surrounded much more by spice/legume crops than by other crops. FFs

with fodder crops were sown independently from the adjacent fodder crops. In non-isolated fields, the distribution of crops was independent of the distribution of adjacent crops.

The differences highlighted in Fig. 7 are confirmed by the correlograms presented in Fig. 8 (continuous neighbourhood metric exploration). The closer the correlation at a given distance is to one, the more frequent two fields at this distance depict the same crop i, which corresponds to an attraction effect at this distance. Conversely, negative and null correlations mean the two fields at this distance depict different crops (repulsion effect) and random crop associations (random effect), respectively. In addition, this continuous neighbourhood metric allows for crop patterns to be inferred: a progressive decrease in the correlogram (as for wheat in isolated fields, see Fig. 8) indicates a patchy pattern for crop i with the average patch diameter corresponding to the range of the correlogram. The range corresponds to the minimum distance where the correlation values fall within the 95% confidence band. However, when there is a significant correlation at a long distance (as for wheat in isolated fields at 800 m, see Fig. 8), it is not interpreted: the small numbers of field pairs at high distances results in the high dispersion of the correlation computation.

The correlation values in isolated fields shown in Fig. 8 indicate a significant attraction effect between wheat fields separated by less than 300 m, whereas the distribution of wheat fields was random at distances greater than 300 m. An attraction effect between spice/legume fields also existed up to a distance of 600 m between fields, although the attraction was less clear. For fodder crops, the attraction effect was visible at very short distances, and the distribution was random at distances greater than 150 m. For non-isolated fields, we observed short-distance repulsion effects or the random distribution of crops.



Fig. 6. Mosaic plot representing the distribution of crops in farmer fields depending on the preceding crop. The independence between the modalities of the previous and current crops according to a Pearson chi-square test is indicated as follows: "+" and "++" indicate a strong and very strong positive dependency, respectively; "-" indicates a strong negative dependency.

3.4. Weight of preceding and neighbouring crops in predicting the allocation of crops to fields

Fig. 9 shows the ability to predict crops in FFs from the "preceding crop" variable and the three variables describing the "adjacent crops". The results indicate that regardless of field context, the explanatory variables significantly improved the prediction of crop types compared to a random distribution. However, the weight of each set of variables tested depended upon the field context. For isolated fields, neighbouring crops and preceding crops had the same weight on crop choice. In non-isolated fields, crop choice depended significantly more on the preceding crop than on the neighbouring crops. In both isolated and non-isolated fields, the use of the entire set of variables permitted us to correctly predict the crops on approximately 60% of the fields.

4. Discussion

4.1. Variability of rules for crop allocation according to the field context

In this study, we inferred statistical rules for crop allocation in accordance with the field context, i.e., isolated and non-isolated fields, that depended upon farmland fragmentation and field dispersion relative to the FFs and the farmstead. For each field context, the rules were defined from a statistical analysis that involved two potential allocation factors: (1) the main preceding crop and (2) the crop distribution in the neighbourhoods of the FFs. In both isolated and nonisolated fields, the preceding crop significantly influenced crop choice, whereas major differences in crop location were observed according to the neighbourhood. In isolated fields, the allocations of wheat and spice/legume crops significantly depended on the neighbourhood, and attraction effects were observed at short distances. In non-isolated fields, the distribution of crops according to neighbouring crops was more random.

We were able to analyse the observed results using informal farmer interviews during the field survey. When farm fields are aggregated

around the farmstead, the farmers can establish their own crop allocation strategy. Then, the allocation constraints are mainly related to the cropping systems, with a strong impact from crop sequences. When farm fields are dispersed far from the farmstead, are not visible from the farmstead and are surrounded by fields belonging to other farms, the farmers must establish a crop allocation strategy in accordance with the ongoing strategies of the neighbouring fields. This strategy permits the management of three main constraints related to crop location. First, most of the fields are not directly accessible by a road or dirt track, and the farmers have to cross other fields to access them. In such cases, particularly for mechanized operations, it is necessary to synchronize the schedule of agricultural operations between fields. Second, synchronization is also necessary to avoid animal-related damage on fields that have not yet been harvested. Animal-related damage is related to the free grazing of fodder crops or crop residues in adjacent harvested fields because shepherd supervision is not always effective. Third, most farmers outsource mechanized operations, such as tillage and the harvest of cereals or fodder, to agricultural contractors. Synchronizing these operations between neighbouring fields simplifies the outsourcing.

Combined with these constraints, the characteristics of the different crops in terms of cropping calendar and location in the crop rotation explain why, according to our results (Figs. 7 and 8), the attraction effects between fields with the same crop type are mainly concerned with wheat on the one hand, and with spices/legumes on the other hand. As seen in Fig. 2, wheat is the last crop to be harvested in the area. This characteristic leads farmers to favour the clustering of wheat fields. In most cases, wheat succeeds spices/legumes (Fig. 6), which in turn leads to the regrouping of spice/legume fields to prepare for wheat sowing the following year. According to the interviewed farmers, regrouping spices and legumes is possible despite the different harvesting dates because these crops are manually harvested and because coriander, which is harvested later than the other crops within this group, does not attract animals.

The absence of a significant impact from the type of neighbouring



Fig. 7. Distribution of crops on farmer fields as a function of crops on adjacent pieces of land, in accordance with the field context. For example, for 80% of isolated wheat fields, at least 20% of the adjacent land consisted of wheat fields.

crops in terms of the spatial distribution of fodder crops (Figs. 7 and 8) may also be explained by the proper characteristics of this group of crops. The harvesting period (from February to June) depends on the type of fodder produced: grazed fodder, dry hay or grain (Fig. 2). Therefore, according to the interviewed farmers, different locations in space and the succession of crops are possible for fodder crops. When devoted to grazing, they are mainly cultivated as a monoculture (i.e., with fodder crops succeeding fodder crops) in areas located near the

farmsteads or in areas characterized by shallow soil or sloping land that are dedicated to fodder production. When devoted to dry hay production, fodder crops may also be located close to fields of spices/legumes that have more or less the same harvesting dates and are used as a preceding crop for wheat. When devoted to grain production, fodder crops may be used as a preceding crop for spices/legumes and will be sown close to wheat areas. The declarations by farmers concerning the location of fodder crops in the succession of crops were corroborated by



Fig. 8. Correlogram for each type of crop in accordance with the field context.

our results in terms of crop sequences for the 2014–2015 and 2015-2016 crop cycles (Fig. 6). Fodder crops preferentially followed fodder crops, but they also preceded or followed wheat and spices/legumes.

This analysis echoes the observations or hypotheses made by agronomists, geographers and historians that have been used to explain the collective cropping plans that were characteristic of the open field landscapes in Europe for more than one thousand years (Caput, 1956; Watteaux, 2005; Calvo-Iglesias et al., 2009; Renes, 2010; Leturcq, 2014) or were still observed in the twentieth century or in the beginning of the twenty-first century in some regions of the world, such as the Serer region in Senegal (Pelissier, 1953) or the Peruvian Andes (Hervé et al., 2002). Fragmented farms, unclosed plots, low-density path networks, and free pasturing on fallows and stubbles after harvest are regularly presented in the aforementioned studies to explain the division of arable lands in different areas, within which farmers had individual fields. Each year, each area was allocated to one of the crops (or types of crop) of the rotation or fallow when fallow was still practised.

4.2. Remaining unexplained variability

The explanatory variables that were addressed in the current study



Fig. 9. Boxplots of good prediction rates obtained from a random distribution of crops and three predictive models of isolated and non-isolated fields. Random: random distribution: Neighb: model based on the variables describing the adjacent crop types; Preced: model based on the "preceding crop" variable; Neighb. & Preced: model based on the adjacent and preceding crops variables. The horizontal lines within the boxes represent the median values, and the square dots represent the mean values.

could explain a large part of the observed variability in crop allocation at the field scale. Nevertheless, 40% of the variability remained unexplained. We must further explore other variables that were reported as potential drivers in previous studies (e.g., Joannon et al. 2008; Thenail et al. 2009; Morlon and Benoît, 1990).

In particular, we should further test several variables that reflect the variability of biophysical conditions at the field scale, such as slope or soil characteristics (e.g., texture, depth, available water capacity). Slope can be calculated from available digital elevation models (DEMs), with some precautions regarding border effects and DEM resolution (Schoorl et al. 2000). The evaluation of soil characteristics is currently difficult because of the lack of data at an appropriate scale. The resolution of the available soil maps (IAO, 2002) is too coarse (1/50000) relative to the mean size of the fields (<1 ha), whereas the available data on soil available water capacity must still be spatially extrapolated and mapped.

Moreover, interest should be paid to the variables that will allow for the better characterization of the field context. In this study, the field context was restricted to a characterization of the field location relative to the other farm fields and the farmstead. Our results suggest the need to precisely describe for each field (1) the accessibility, (2) the existence of linear elements (cactus hedge, ditches, banks, etc.) that mark a limit between adjacent fields and permit field protection against possible damage from herds and (3) the visibility from the farmstead. In the near future, thanks to the development of techniques for acquiring and processing very high spatial resolution satellite images (Fauvel et al., 2013; Sofia et al., 2016), the automated acquisition of path networks and other linear elements might be possible and would help define a more precise field context indicator. Visibility from the farmstead could be evaluated with digital surface models (DSM) that incorporate the heights of the elements above the terrain (Floriani and Magillo, 2003).

At the farm level, the impacts of production strategies and farmer resources on crop locations remain to be assessed. In particular, attention should be paid to the different uses of fodder crops and their relations with livestock. However, our results indicate that in the context of land fragmentation, the farm scale may not be sufficient to understand farmer decision-making. As noted by Morlon and Trouche (2005), there is a need to account for the relationships between neighbouring farmers. Existing differences between isolated and non-isolated agricultural fields and declarations of the interviewed farmers suggest that in the Lebna watershed, crop aggregates are not managed at the village scale. This finding is contrary to what has been observed in areas such as the Peruvian Andes (Hervé et al., 2002) or Senegal (Pelissier, 1953) or to what is commonly accepted as the typical management of the ancient open fields in Europe (Watteaux, 2005; Calvo-Iglesias et al., 2009; Renes, 2010; Leturcq, 2014). In the Lebna watershed, crop aggregates concern groups of farmers who exploit the same zones regardless of their places of residence. Therefore, defining the limits and understanding the functioning of these groups is a necessity to improve our understanding of the factors driving crop allocation.

4.3. Towards characterization of spatiotemporal patterns of crop allocation at the watershed scale

The extrapolation of our results would require validation over time (several successive years) and space (at the watershed scale). For this, remote sensing is a powerful tool that can be used to describe the patterns of crop distributions at the landscape scale and allows for the quantification of their variability in time and space. Remote sensing techniques are now able to provide times series data on the land use patterns of small farm landscapes (Inglada et al., 2015). The combined use of remote sensing data and data collected from field observations and interviews with farmers will allow for future improvements to our characterization and understanding of both farmer strategy for crop allocation and spatiotemporal patterns of land use.

5. Conclusions

Our study revealed the significant effect of farmland fragmentation

on farmer decision-making for crop allocation within a northern Tunisian rainfed watershed that is dominated by annual fragmented cropland. When fields are dispersed, farmers implement, with some of their neighbours, collective rules of crop allocation that permit the management of common constraints. At the landscape scale, the consequence is the presence of field aggregates with the same crop type.

These results indicate that to improve our understanding of the drivers of crop allocation at the landscape level, it is not sufficient to only address the rules and drivers at the field and farm scales, but it is also necessary to account for the collective contexts in which farmers operate. Thus, our findings underline the need to deepen our knowledge of the existing agreements between farmers to refine our understanding of crop allocation.

For a better overview of driver complexity, other potential drivers should also be assessed, including production strategies, farmer resources, and the precise characteristics of their fields. In addition to biophysical drivers, the assessment of variables related to field accessibility, visibility and protection against animal damage is necessary. In the future, by permitting access to these variables and describing the spatiotemporal patterns of crop location at the watershed scale, remote sensing will help improve our knowledge of farmer decision-making. Conversely, knowledge of farmer decision-making and its drivers will improve our understanding of the regionally observed patterns.

A possible operational outcome from this approach and the obtained results is the integration of crop allocation drivers in land use prediction models. This integration will permit the simulation of plausible land use scenarios and the assessment of their subsequent ecosystem services. Overall, the identified drivers should also be perceived as constraints to be considered when defining public and/or agricultural policies. The collective rules of crop allocation that were observed in our study indicate that any public policy favouring the spatial alternation of crops at the landscape scale to increase ecosystem services could face difficulties because of the organizational constraints of farmers related to farmland structure.

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