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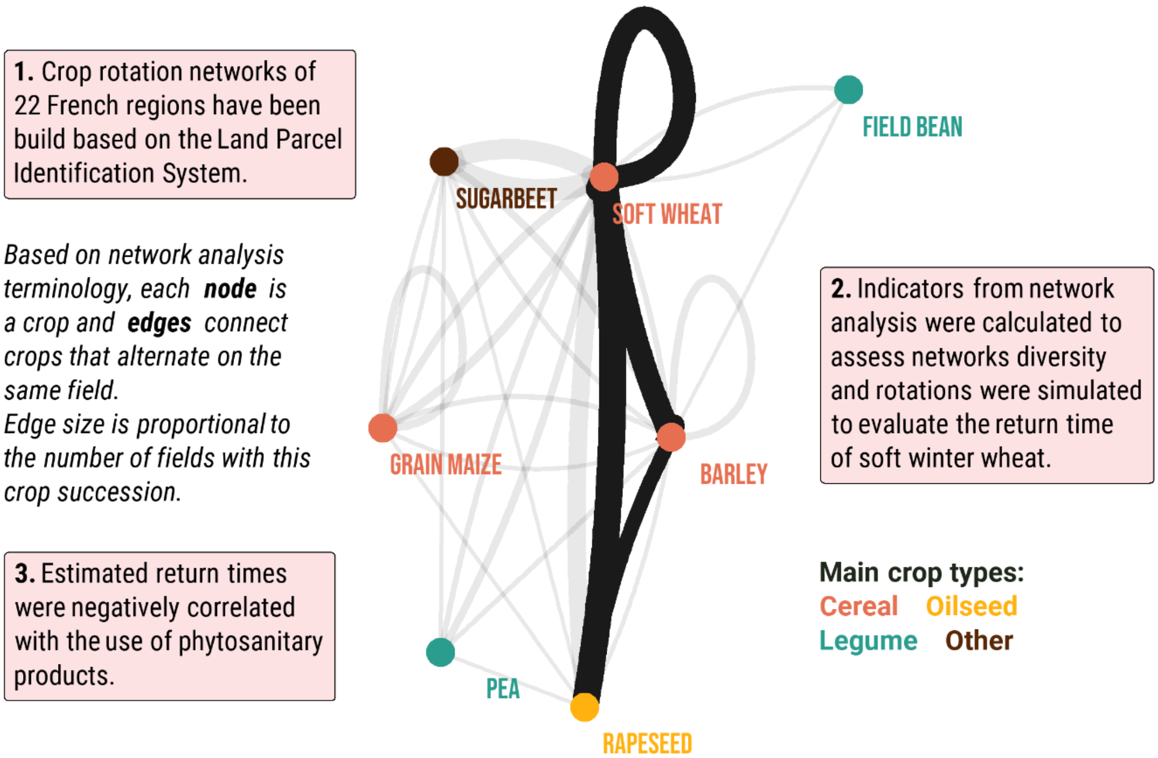
Graphical Abstract



Keywords

Crop rotations; Network analysis; Cropping systems; Winter wheat; Crop protection

Abstract

CONTEXT

More diversified crop rotations are a key factor in reducing weed, disease and pest pressure while reducing the use of phytosanitary products. The increase in available data calls for the development of new methods and indicators to characterize crop rotations.

OBJECTIVES

This paper presents an application of network analysis to assess the diversity of crop rotations from the Land Parcel Identification System, which now provides field boundaries and type of crops grown in a given year for farmers receiving subsidies from the European Common Agricultural Policy. Different indicators are presented to compare the diversity of crop rotations for the 22 regions of mainland France (corresponding to the boundaries of former administrative regions) and the influence of some methodological choices are discussed.

METHODS

Using LPIS data, previous-following crop pairs have been identified for two thirds of the French fields for three crop successions (from 2017 to 2018, from 2018 to 2019 and from 2019 to 2020). These data were used to build crop rotation networks for each region. Crop rotations were simulated from those networks in order to estimate the return time of soft winter wheat, which is the most cultivated crop in the country.

RESULTS AND CONCLUSION

Crop rotation networks were similar between the three crop successions compared, but differed among regions. Ignoring the most uncommon previous-following crop pairs, the mean number of precedents per crop ranged from three to nine depending on the region. The estimated return times for winter wheat increase when taking into account grasslands in crop rotation networks, but in any case the use of phytosanitary products was negatively correlated with the return time.

SIGNIFICANCE

The methodology developed in this article provides some initial guidelines for developing relevant agronomic indicators from crop rotation network analysis. It has been shown that the estimated return time could be an indicator of the intensity of use of phytosanitary products, and could therefore be used to guide public policies aimed at reducing the use of these products.

1. Introduction

Diversified and longer crop rotations are a key factor in reducing weed, disease and pest pressure while reducing the use of phytosanitary products (Kremen et al., 2012). The identification of crop rotations is therefore important for assessing the sustainability of farming systems. Yet data at field scale are rare, which limits the possibility of determining crop rotations. To overcome this lack of data, crop rotation simulation models have been developed based on agronomic rules (Bachinger and Zander, 2007; Stein and Steinmann, 2018). Another approach explored to estimate crop rotations was land cover classification using remote sensing and deep learning (de Abelleyra and Verón, 2020; Plourde et al., 2013).

In Europe, an important data source is the Land Parcel Identification System (LPIS) of the Common Agricultural Policy, which provides the boundaries of cultivated areas and type of crops grown in a given year for farmers receiving subsidies from the Common Agricultural Policy. Several studies have been conducted using this database. For the Walloon region in Belgium, Leteinturier et al. (2006) developed a set of agro-environmental indicators to compare crop rotations. More recently, Levavasseur et al. (2016) designed a software, called RPG Explorer, which allows the extraction of rotations for a given territory.

Before 2015, LPIS data were only available at the block level (i.e. a group of close fields that are cultivated by the same farmer, but that can be cultivated with different crops the same year), so decision rules had to be implemented to estimate the distribution of crops within the blocks. As these rules can be cumbersome to define and depend on local conditions, these studies have generally been conducted at the scale of small territories , for example at the watershed scale (Rizzo et al., 2019).

New data sources currently available, such as field-scale data in the European LIPS or the identification of crops through remote sensing (d'Andrimont et al., 2021), facilitates crop identification, making it possible to extrapolate rotations to larger areas, such as the national level. These recent developments encourage the elaboration of new methods and indicators to characterize crop rotations.

Methods from network analysis have previously been used in agriculture to assess the effect of farm networks on the diffusion of knowledge (Isaac, 2012), the propagation of livestock diseases (Dubé et al., 2009; Natale et al., 2011) or nutrient cycling at the farm scale (Rufino et al., 2009) or territory scale (Nowak et al., 2015). Regarding crop rotations, previous studies have presented theoretical mathematical frameworks based on network analysis to define an optimal crop rotation for a given selection of crops on a given field (Castellazzi et al., 2008; Detlefsen and Jensen, 2007). More recently, this work has been extended to improve the identification of crops from satellite images, taking into account the main crop rotations (Osman et al., 2015).

This investigation builds on these previous examples and proposes an application of network analysis to identify crop rotations for a given territory. Crop rotation networks were built at the regional scale using data from the French LPIS. These rotations were then compared using different indicators from network analysis. In particular, the return time of soft winter wheat, which is the most cultivated crop in the country, was estimated for each region from simulations of crop rotations.

2. Materials and methods

2.1. Creation of transition matrices

LPIS from 2017 to 2020 were used to determine crop rotations for the 22 regions of mainland France for three crop successions (from 2017 to 2018, from 2018 to 2019 and from 2019 to 2020). Concerning the regions, it was chosen to use the boundaries of the former administrative regions of France, because many statistical data are still made available for these regions (Agreste, 2020).

The French LIPS contain an attribute "ID_PARCEL" which allows to identify each field, and thus to follow its evolution from one year to another. This association could only be carried out for part of the fields because the borders of some of them were modified from one year to the next. The percentage of fields with information about the previous crop was stable for three periods studied, with two thirds of the fields being kept in each period (i.e. approximately two million fields out of a total of three million in France). This ratio was similar in terms of the area studied (i.e. approximately 8.4 million hectares out of a total of 13.7 million). For each field and each year, the crop classification was performed according to the “CODE_CULTU” attribute (see **Supplementary materials**).Once the previous crops were identified for each field, transition matrices were established for each region by calculating the probability of switching from one crop to another (**Figure 1**).

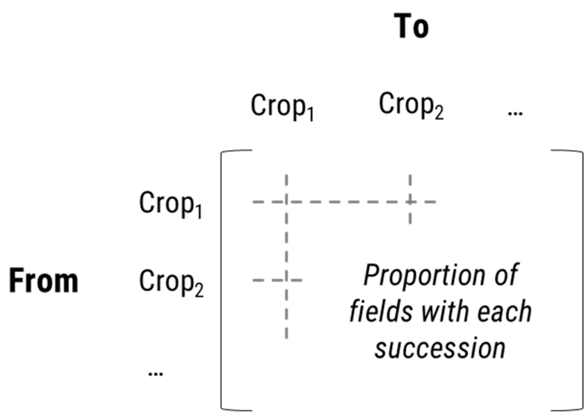


Figure 1 *Example of the calculation of transition matrices*

2.2. Assessment of indicators related to network analysis

In network analysis, density is defined as the number of edges in the network divided by the maximum number of edges possible for the network. Thus, for a directed network, the density, d, is calculated as follows:

$$d = \frac{m}{n(n-1)} \qquad \text{(Eq. 1)}$$

Where m is the number of edges in the network and n the number of nodes. For the networks of this study, the nodes correspond to the crops and the edges to the switches from one crop to another on the same field.

The second indicator calculated in this study is the mean number of in-degrees (i.e. number of incoming edges per node) per region. To simplify the interpretation of the results, this indicator will hereafter be referred to as the mean number of precedents per crop.

The third indicator is the mean return time for soft winter wheat. This last indicator focuses on winter wheat because it is the crop cultivated on the largest area in France. This crop is cultivated on 4.7 million hectares, more than a quarter of the country's arable land (Agreste, 2019). The mean return time was calculated from simulations of crop rotations based on the transition matrices (see **Graphical Abstract** for a visual example of a simulation of a short rotation).

Starting with wheat in year 1, the crop of year 2 is determined from a random draw based on the probabilities given by the row corresponding to wheat in the transition matrix. Likewise, the crop of year 3 is determined by a random draw according to the transition probabilities given by the year 2 crop line and so on.

For each region, 100 rotations of 100 years were performed and the return time of wheat was estimated as the median return time of this crop for all these rotations.

2.3. Sensitivity to network design

To limit the study to the most representative rotations, only the previous-following crop pairs present on at least 0.05% of the fields of each region have been retained. Furthermore, the choice was made to focus on crop rotations with only field crops (e.g. wheat, maize, rapeseed), excluding grasslands, because this type of rotation accounts for the vast majority of grain production in France. The influence of these decisions will be discussed in the **Results** section, but in the absence of remarks to the contrary, the results given were obtained by applying these decision rules.

2.4. Comparison with agronomic indicators

The return times estimated with the method described above were then compared to main source of statistical data on the use of phytosanitary products in France: the surveys on farmers' cultivation practices which were last carried out in 2017 (Agreste, 2020).

All data processing was done with the R software (R Development Core Team, 2009). Graphs and analysis of the networks were carried out with the libraries {ggraph} (Lin Pedersen, 2021), {tidygraph} (Lin Pedersen, 2020) and {igraph} (Csardi and Nepusz, 2006).

3. Results

3.1. Converting crop rotations into networks

With no threshold for the relative importance of the previous-following crop pairs, differences in crop rotation networks between regions seem limited (**Figure 2**). All networks appear to be densely connected. But this hides the fact that a large proportion of crop successions are carried out on only a very small number of fields. Important difference between regions appear when removing the previous-following crop pairs present on less than 0.05% of the fields of each region. For instance, the crop rotation network for the Rhône-Alpes region appears more densely connected than that of the Champagne-Ardennes region.

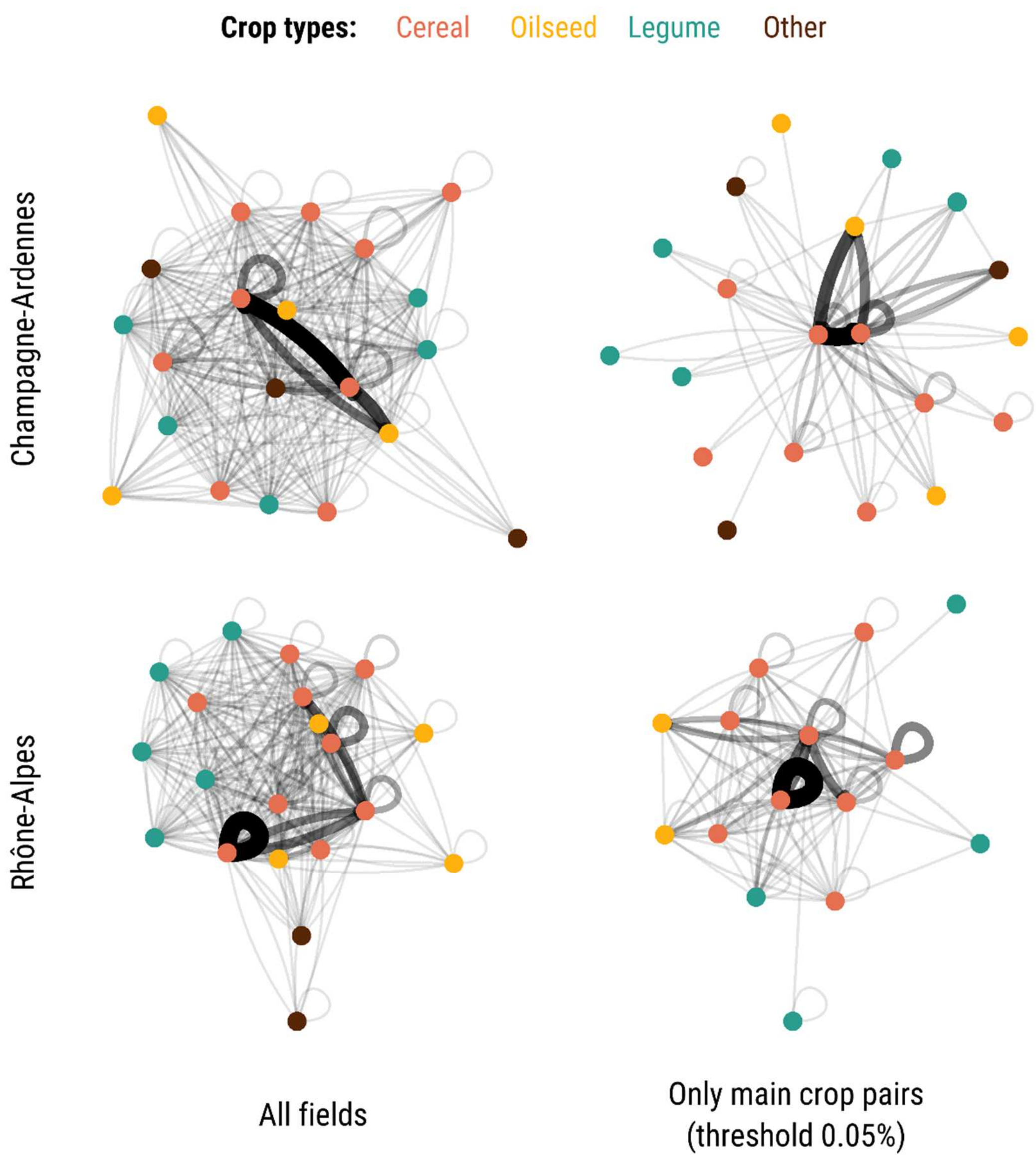


Figure 2 *Comparison of crop rotation networks for two regions (vertical axis) according to the relative importance of the previous-following crop pairs retained (horizontal axis). A threshold of 0.05% means that only the previous-following crop pairs present on at least 0.05% of the fields in the region have been retained. Size of links between crops is proportional to the number of fields with this crop succession. The position of the crops corresponds to their importance in the rotations, with the most important ones in the center. Crop rotations networks represented here correspond to the succession between 2019 and 2020 but the same trend was found for the three successions considered.*

For Champagne-Ardennes, there are two cereal crops alternating with an oilseed crop in the heart of the network. This pattern corresponds to the rapeseed then winter soft wheat then barley succession, which is the most common crop rotation in France. For Champagne-Ardennes as for Rhône-Alpes, legume have a relatively minor place in the rotations, which can be seen in their position on the periphery of the networks. Because of the small difference in crop rotation networks between years, the next results will be presented only for the succession from 2017 to 2018.

3.2. Indicators related to crop rotation networks

Figure 3 represents different indicators related to crop rotation networks of the French regions. The first indicator (**Figure 3a.**) is the density, i.e. the ratio between the number of connections established and all possible connections in the network. Value of the indicators ranged between 0.17 and 0.58. The implication of this indicator can be illustrated by the comparison between the two regions highlighted in **Figure 2**, with a density of 0.25 for Champagne-Ardennes and 0.58 for Rhône-Alpes. In other words, this means that 58% of all possible previous-following crop pairs were realized in the Rhône-Alpes region.

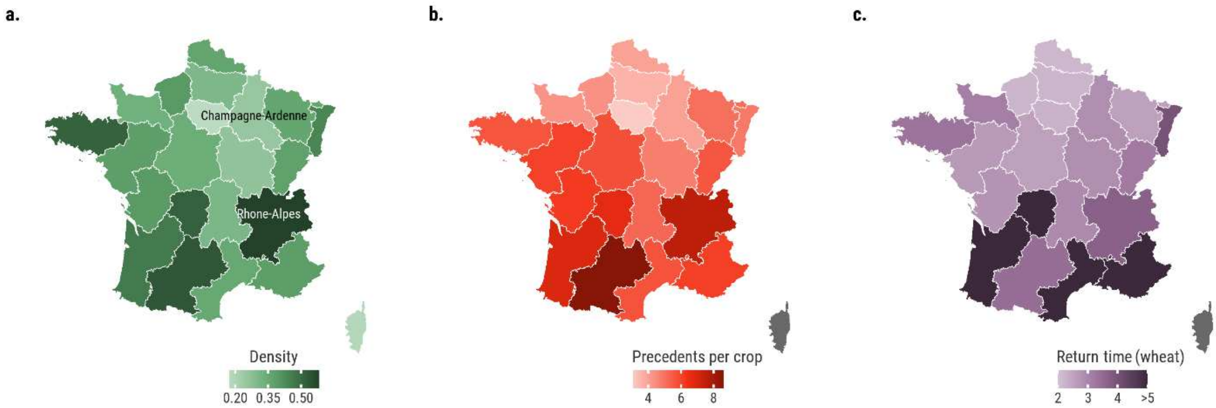


Figure 3 *Mapping of three indicators (a. Density, b. Mean number of precedents per crop and c. Return time for soft winter wheat) related to the crop rotation networks of French regions for the crop succession from 2017 to 2018. There was not enough data available to establish the crop rotations for the shaded region (the island of Corsica).*

The second indicator (**Figure 3b**) is the mean number of precedents per crop. This indicator varied from three to nine depending on the region (about four for Champagne-Ardenne and eight for Rhône-Alpes). As this indicator is strongly correlated with density, the two maps **Figure 3a** and **Figure**

3b were relatively similar, but mean number of precedents per crop gives a value that is more directly interpretable from an agronomic point of view.

Unlike the first two indicators, which were calculated for the whole networks, the last one focuses on a single crop, with the estimation of the number of years before the return of soft wheat on the same field (**Figure 3c**). Again, the return times for soft winter wheat are generally higher for regions with high density networks (about four years for the Rhône-Alpes region versus 3 years for Champagne-Ardenne). However, some regions with low densities may also have high return times for soft wheat. This is mainly the case for the regions bordering the Mediterranean Sea (in the south of France) and this can be explained by the low importance of soft wheat in the crop rotation of these regions.

3.3. Relationships between network indicators and agronomic indicators

Compared to the map in **Figure 3c**, only the 17 regions with statistics on the use of phytosanitary treatments on winter soft wheat were kept to study the relationship between the estimated return time and the phytosanitary treatment frequency index , leaving out the five regions for which this crop is less important in crop rotations. Moreover, while the previous map presented the estimated return times taking into account only crops, **Figure 4** also presents the estimated return times with grasslands in the crop rotation networks. Despite the fact that the rotation between grasslands and crops represents limited areas, including temporary grasslands increases the return time, because these forages are generally implanted for several years in a row. But in both case a strong relationship was found between the estimated return time and the phytosanitary treatment frequency index of soft winter wheat. More precisely, when considering rotation networks with only crops, the use of phytosanitary products decreased by half (from six to three doses applied) with the doubling of the return time (from two to four years).

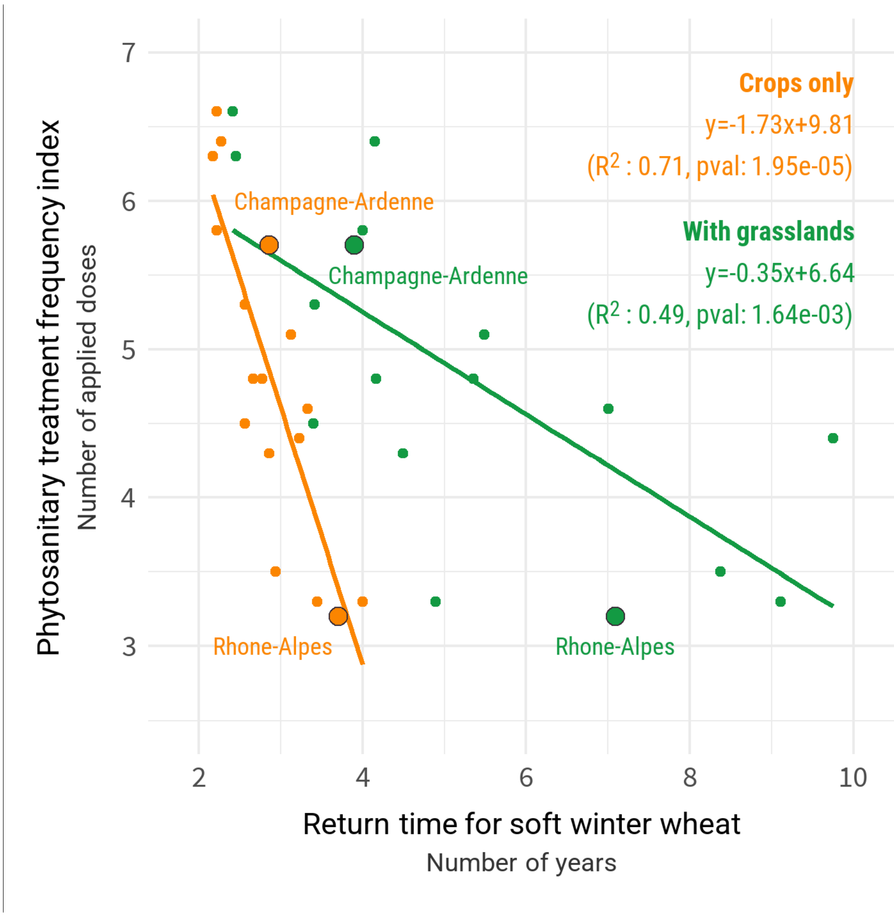


Figure 4 *Relationship between estimated return time and phytosanitary treatment frequency index for soft winter wheat, depending on whether or not grasslands are taken into account in crop rotation networks to estimate the return time of wheat. Each dot represents a French region, with the two colored points corresponding to the regions highlighted in Figure 2.*

4. Discussion

The application of network analysis to identify crop rotations for French regions showed that the difference in crop rotation diversity was high among regions (**Figure 2**). The analysis conducted here showed that the mean number of precedents per crop could vary from three to nine between regions (**Figure 3b**).

Regarding the limitations of this study, these values are only relevant at the regional scale. For example, the mean number of crop precedents is probably much lower when calculated at lower scale, such as the farm scale. Network analysis is strongly dependent on the theoretical framework chosen to represent the investigated issue (Bockholt and Zweig, 2020), as shown in **Figure 2**. Taking into account all previous-following crop can lead to the perception of very diversified rotations whereas certain combinations only appear on one or a few fields.

The design of crop rotation networks must thus be adapted to each problematic. Here it has been shown the difference in the estimated return time of soft winter wheat depending on whether or not grasslands are integrated in the rotations (**Figure 4**). As phytosanitary products use is higher on arable farms than on animal farms (Bürger et al., 2012; Herzog et al., 2006; Jørgensen et al., 2008), it may be appropriate to exclude grasslands when considering the impact of crop rotations on the use of these products. But another study looking at crop-livestock relationships will need to include grasslands in the rotation networks.

Not all combination of crop succession are favorable, and some should be avoided, but to some extent it can be assumed that long and diverse crop rotations are favorable to cropping systems durability (Kremen et al., 2012). With or without the inclusion of grasslands in the networks, this study has shown that the use of phytosanitary products was negatively correlated with the estimated return time of soft winter wheat (**Figure 4**). This indicator could therefore be used to guide public policies aimed at reducing the use of these products. More generally, the methodology developed in this article provides some initial guidelines for developing relevant agronomic indicators from crop rotation network analysis.

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Supplementary materials

The table below details the classification of crops used in this study. The column 'CODE_CULTU' corresponds to the definition of the crop in the French LPIS while the column 'Crop classification' gives the crop definition for this study. Overall, compared to the French LIPS, this study does not distinguish between spring and winter crops for the same species. Furthermore, in order not to multiply the number of previous-following crop pair, the least frequent crops of each major family have been aggregated into an 'Other' category ('Other cereal', 'Other legume' or 'Other oilseed').

Family	CODE_CULTU	Crop classification
Cereal	BTH	Soft winter wheat
	BTP	Soft spring wheat
	MIS, MID	Grain maize
	MIE	Silage maize
	ORH, ORP	Barley
	AVH, AVP	Oat
	BDH, BDP, BDT	Hard wheat
	TTH, TTP	Triticale
	SOG	Sorghum
	CAG, CGF, CGH, CGO, CGP, CGS, CHA, CHH, CHS, CHT, CPA, CPH, CPS, CPT, EPE, MCR, MLT, SRS, SGH, SGP, RIZ	Other cereal
Oilseed	CZH, CZP	Rapeseed
	TRN	Sunflower
	LIH, LIP	Linen
	MOL, NVE, NVH, OAG, OEH, OEI, OHN, OHR, OPN, OPR, CHF, NVF	Other oilseed
Legume	SOJ	Soya
	LEC, LEF	Lentil
	FEV, FVL, FVT	Field bean
	PHI, PPR, PPT, PCH	Pea
	LDH, LDP, LDT, MPC, MPP, MPT, PAG, CPL, GES	Other legume
Other crops	BTN	Sugarbeet
	CHV	Fiber hemp
	LIF	Fiber linen