LIFT

Low-Input Farming and Territories – Integrating knowledge for improving ecosystem based farming

Research and Innovation action: H2020 – 770747
Call: H2020-SFS-2016-2017
Type of action: Research and Innovation Action (RIA)
Work programme topic: SFS-29-2017
Duration of the project: 01 May 2018 – 30 April 2022

Spatial dependencies in patterns of adoption at local and regional levels - The case of ecologically-friendly agriculture

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DELIVERABLE D4.1

Workpackage N°4

Due date: M36

Actual delivery date: 20/04/2021

Dissemination level: Public

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 770747

About the LIFT research project

Ecological approaches to farming practices are gaining interest across Europe. As this interest grows there is a pressing need to assess the potential contributions these practices may make, the contexts in which they function and their attractiveness to farmers as potential adopters. In particular, ecological agriculture must be assessed against the aim of promoting the improved performance and sustainability of farms, rural environment, rural societies and economies, together.

The overall goal of LIFT is to identify the potential benefits of the adoption of ecological farming in the European Union (EU) and to understand how socio-economic and policy factors impact the adoption, performance and sustainability of ecological farming at various scales, from the level of the single farm to that of a territory.

To meet this goal, LIFT will assess the determinants of adoption of ecological approaches, and evaluate the performance and overall sustainability of these approaches in comparison to more conventional agriculture across a range of farm systems and geographic scales. LIFT will also develop new private arrangements and policy instruments that could improve the adoption and subsequent performance and sustainability of the rural nexus. For this, LIFT will suggest an innovative framework for multi-scale sustainability assessment aimed at identifying critical paths toward the adoption of ecological approaches to enhance public goods and ecosystem services delivery. This will be achieved through the integration of transdisciplinary scientific knowledge and stakeholder expertise to co-develop innovative decision-support tools.

The project will inform and support EU priorities relating to agriculture and the environment in order to promote the performance and sustainability of the combined rural system. At least 30 case studies will be performed in order to reflect the enormous variety in the socio-economic and bio-physical conditions for agriculture across the EU.

Project consortium

No.	Participant organisation name	Country
1	**INRAE - Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement**	**FR**
2	VetAgro Sup – Institut d'enseignement supérieur et de recherche en alimentation, santé animale, sciences agronomiques et de l'environnement	FR
3	SRUC – Scotland's Rural College	UK
4	Teagasc – Agriculture and Food Development Authority	IE
5	KU Leuven – Katholieke Universiteit Leuven	BE
6	SLU – Sveriges Lantbruksuniversitet	SE
7	UNIBO – Alma Mater Studiorum – Universita di Bologna	IT
8	BOKU – Universitaet fuer Bodenkultur Wien	AT
9	UBO – Rheinische Friedrich-Wilhelms – Universitat Bonn	DE
10	JRC – Joint Research Centre – European Commission	BE
11	IAE-AR – Institute of Agricultural Economics	RO
12	MTA KRTK – Magyar Tudományos Akadémia Közgazdaság – és Regionális Tudományi Kutatóközpont	HU
13	IRWiR PAN – Instytut Rozwoju Wsi i Rolnictwa Polskiej Akademii Nauk	PL
14	DEMETER – Hellinikos Georgikos Organismos – DIMITRA	GR
15	UNIKENT – University of Kent	UK
16	IT – INRAE Transfert S.A.	FR
17	ECOZEPT Deutschland	DE

Contents

List of acronyms and abbreviations

AES: Agri-environmental schemes

BMP: Best Management Practices

EFA: Ecologically-friendly agriculture

EU: European Union

LAU: Local Administrative Units

NUTS: Nomenclature of Territorial Units for Statistics

RDP: Regional Development Programme

UAA: Utilised Agricultural Area

1 Summary

In this document, we present the results of the first meta-analysis of the spatial distribution of ecologically-friendly agriculture (EFA), incorporating systems (e.g. integrated production), bundles of practices (e.g. green control measures) and single practices (e.g. conservation tillage). We opted for a qualitative meta-analysis, as we are mainly concerned with the significance, extent and location of the phenomenon of spatial clustering and/or dispersal, and less so on its absolute quantitative magnitude. Our study has three aims. Firstly, we review the evidence on spatial clustering of EFA practices and systems. Secondly, we conduct a qualitative analysis of the variables that influence the spatial distribution of EFA systems and practices as ascertained using spatial models only. Thirdly, and finally, we conduct a qualitative analysis of the variables that have a spatial spillover effect, i.e. farmer or administrative unit characteristics that can influence neighbouring farmers or administrative units. We maintain a local and regional focus throughout the study. We performed a literature search on Scopus, and after retrieving circa 6000 documents, we narrowed down our sample to 39 relevant papers published in peer-reviewed journals. From this sample we reviewed the evidence on spatial clustering across EFA practices and systems, and recorded methodological aspects of the literature. To analyse the factors that influence the spatial distribution of EFA systems and practices, we focused on those studies that used some kind of formal spatial statistical test to study those processes, a total of 26 studies. Finally, we focused on eight studies that used spatial statistical models suited to the study of right-hand side spillover effects, to study the variables that have spatial neighbourhood effects. We found that geographical and farming system biases in the literature hinder global and regional/local understanding. We also found that spatial clustering is a prominent feature of EFA systems and practices, although perhaps not as universal as commonly presented - especially at the local and regional scales and modulated by crop, system, and geographical context. By reviewing the variables that influence EFA systems and practices adoption or uptake, we argue that while some variables do seem to have a clear effect, more research is needed for the majority of variables – especially regarding variables that might have spillover effects. Arguably, this is not just a case of more research along previously followed lines, but research that focuses on different locales and scales, diverse systems and practices, and using both (the right) quantitative and qualitative methodologies.

2 Introduction

Farming activities, practices and agricultural systems are organised in space. In this qualitative meta-analysis, we review the geographical distribution of ecologically-friendly farming (EFA). Our review encompasses – broadly defined – EFA systems (e.g. organic farming, integrated production), bundles of management practices (e.g. integrated pest management), and individual management practices (e.g. no tillage). It is thus the first comprehensive meta-analysis of the literature on the spatial organisation of EFA.

Our review has three straightforward aims. Firstly, to review the evidence on spatial clustering of EFA farming practices and systems, and explore under which conditions clustering occurs. By conditions we refer to both "system features" such as crop/livestock types or farming systems, and methodological choices, such as resolution or scale of analysis. On this respect we also provide an assessment on whether this clustering is environmentally and/or policy driven (e.g. due to soil type), or whether it is an effect of social interactions and/or agglomeration effects (e.g. neighbour spillover effects). Secondly, we provide a qualitative analysis of the variables that influence the spatial distribution of EFA systems and practices as ascertained using spatial models only. This is particularly important since variable significance, coefficients and sometimes even signs differ between a-spatial and spatial models in cases where spatial dependencies occur (Case 1992; Parker and Munroe 2007; Bonfiglio and Arzeni 2019). Thirdly, we provide a qualitative analysis of the variables that have a spatial spillover effect, i.e. farmer or administrative unit characteristics that influence neighbouring farmers or administrative units.

Overarching trends in the spatial distribution of EFA systems and farming practices have not been investigated. Furthermore, with the exception of Malek et al. (2019) who studied the global and national spatial distribution of organic farming, no other study has attempted to systematically review or statistically analyse the factors which affect the spatial distribution of EFA. Mozzato et al. (2018) have a similar focus to ours regarding 'environmentally friendly farming practices', however their aim is to study factors influencing adoption and not spatial patterns of adoption. Furthermore, our work, by focusing solely on spatial models overcomes a central limitation of Mozzato et al. (2018) who, in listing the caveats of their study, note that 'the main one [is] linked to the different methodological approaches adopted by the papers reviewed' (ibid, p. 10). Linked to this caveat is the conflation of spatial and a-spatial models in Mozzato et al. (2018) and other reviews (see meta-review of Liu et al. 2018 and references therein), since EFA systems and practices are often characterised by spatial dependence, and a-spatial models are not always suited to the task (although see Swinton 2002).

Such a lacuna is important for a variety of reasons. Firstly, to better understand EFA's intersections with local physical environments and cultures (Getz and Shreck 2006), particularly as different socio-ecological systems often beget different adoption patterns and processes, e.g. for climate friendly agriculture (e.g. Nguyen and Drakou, 2021). Secondly, to be able to provide more detailed information to policy makers targeting agri-environmental schemes, incentives or information campaigns regarding neighbour effects and farmer telecoupling (Zimmerer et al. 2018). Thirdly, to allow for coordination between agri-environmental schemes (AES), payments for ecosystem services and other related incentives (Sutherland et al. 2012).

3 Conceptual and methodological background

There are two general processes driving spatial dependence in EFA: spatial autocorrelation and spatial heterogeneity (Schmidtner et al. 2012; Yang et al. 2014; after Anselin 1988). Spatial heterogeneity refers to variation across space, indicating that there are spatially distributed factors driving the spatial pattern of EFA practices, activities and/ or systems. For example, in targeted AES, some management options are available only in particular areas therefore causing spatial clustering of these particular options to these targeted areas. Another example could be the prevalence of organic farming on less productive soils (Lewis et al. 2011; Gabriel et al. 2009).

Spatial autocorrelation is related to Tobler's law of geography, that 'everything is related to everything else, but near things are more related than distant things' (Tobler 1970, p. 236). In everyday terms, it means that there is a 'relationship of what happens at one point in space and what happens elsewhere' (Anselin 1988, p. 11, in Schmidtner et al. 2012). There are many conceptual understandings and schemas of why EFA systems and practices display these types of spatial characteristics. At the farmer level, understanding the spread of agricultural practices as technology and innovation diffusion, pioneering geographer Thorsten Hägerstrand (1967 [1953]) concluded that local communication between farmers is a powerful agent of technology diffusion across rural spaces – the 'neighbourhood effect' (*ibid*). Viewing organic agriculture as an 'example of the diffusion of an innovation' (Padel 2001, p. 40), various scholars have studied adoption/diffusion processes using – broadly understood and extended – Hägerstrand's schema, incorporating social networks (Nyblom et al. 2003) or time-space diffusion (Van der Horst 2011). In cases such as this, the decision of a farmer to convert to some type of environmentally-friendly practice is viewed as an innovation that is strongly 'correlated [negatively or positively] with the decisions of "the closer" farmers and their characteristics' (Boncinelli et al. 2017, p. 56). As Roger Bivand (Bivand 2015, p. 106) succinctly puts it: 'farmers are more likely to adopt innovations if they are in close proximity to earlier adopters'. These effects, called spillover effects, if positive, mean that a farmer's decision to adopt environmentally-friendly agriculture is higher if his/her neighbours have also adopted it.

At larger spatial scales, there are additional factors driving spatial spillover effects. Correlation here is not present between "neighbouring" farmers, but "neighbouring" areas – often studied at low administrative scales (e.g. Schmidtner et al. 2015; Marasteanu and Jaenicke 2016). At a local scale, Ilbery and Maye (2011) give a plethora of drivers of clustering, including the diffusion and neighbourhood effect just mentioned, but also the existence and membership of cooperatives and certifying bodies, the existence of pioneering and champion farmers and ambassadors, and the encouragement of community networks and the marketing channels for environmentally-farmed produce. At regional scales, Schmidtner et al. (2012) propose that along with the above drivers, agglomeration effects and economies of scale are also present. While as Schmidtner et al. (2012) note such an understanding does not directly translate to agricultural activities, they give some examples: 'agglomeration effects due to direct communication or – probably more often – resulting from local institutions or markets do indeed play a role for some agricultural specialities, such as organic farming' (*ibid*, 662) or 'when an agglomeration of a certain farming system leads to a larger pool of experience that entrepreneurs can draw upon' (*ibid*, 666).

Taking stock of the above, we focus our results on the following. Firstly, throughout, we pay particular attention to the scale of phenomena and analyses. We hypothesise that as scale of analysis increases, the spatial heterogeneity of factors affecting the spatial distribution of EFA systems and practices also increases. This includes both environmental factors such as soil or climate, economic factors such as closeness to organic markets or competition in output markets, and policy-related factors such as the existence of protected areas or targeted AES. In practical terms, this means that our hypothesis is that we expect to see more clustered distribution at the international or national scale of analysis than at the local or regional scale. Secondly, following the innovation diffusion hypothesis, we expect to find spatial spillover effects related to knowledge-related factors. For example, we expect that at the farm level of analysis, variables such as farmer education would have a effect on their neighbouring farmers. Thirdly, we expect that different EFA systems would have different spatial distribution patterns, and their adoption would be affected by different factors, even at the same place. The same holds for different crops, or even single practices.

As alluded above, the quantitative study of spatial patterns of EFA systems and practices was pioneered and influenced by quantitative geography, and secondarily by regional science and spatial (agricultural) econometrics. Methodologically, there are two main foci in the literature. One, which is the earliest, is the documentation of spatial inequalities in the number of organic farms or organic utilised agricultural area (UAA) at the national scale, often calculated using some kind of spatial statistics such the location quotient (Cudjoe and Rees 1992; Ilbery et al. 1999; Frederiksen and Langer 2004; Gabriel et al. 2009), (global) Moran's I (Marasteanu and Jaenicke 2016; Zasada et al. 2018) or econometric inequality indices such as the Lorenz curve (Hrabák and Konečný 2018). A related methodology is the identification of local clusters, often using local Moran's I (often called LISA; Boncinelli et al. 2016; Lu and Cheng 2019). Second, the identification of factors driving the spatial distribution of EFA, which is usually estimated using statistical models with spatial components, either spatial lags of the dependent variable (spatial lag models), the error terms (spatial error models), or the independent variables (spatial lag of X models, SLX), or some combination of the above (spatial Durbin models, SDM). The latter two, SLX and SDM, allow for the identification of spillover effects from the right-hand side variables, which can be important factors in the adoption or uptake of EFA systems and practices.

4 Methodology

We first conducted a simple search ('"spatial clustering" "spatial agglomeration" agriculture conservation organic') on Google Scholar, downloaded and read a first set (15) of papers to gain an understanding and familiarise ourselves with the terms used in the literature. Then, using trial and error, we devised the following search string and employed it to search the Scopus bibliographic database (latest update on December 17, 2020:

> *(TITLE-ABS-KEY (spatial* OR "neighbo*" OR "network ana*" OR "Network Ana*" OR "Neighborhood effect" OR "neighborhood effect" OR "Neighbourhood effect" OR "neighbourhood effect") AND (TITLE-ABS-KEY ("organic farm*" OR "organic agri*" OR "agri-envi*" OR agrienvi* OR "sustaina* farm*" OR "sustaina* agri*" OR "sustaina* practi*" OR "alternativ* farm*" OR "alternativ* agri*" OR "alternativ* crop*" OR "agrobiodiversi*" OR "agro-biodivers*" OR "rural development" OR "management practice*" OR "best management practice*" OR "green control techniques" OR "farming practic*" OR "integrated farm*" OR "integrated agricul*")) AND (TITLE-ABS-KEY ("agri*" OR "farm*" OR "devel*"))*

We downloaded 5982 papers. Based on title scanning we excluded 5640 papers. For the remaining papers we read the abstracts and excluded a further 242 papers. For the rest of the papers, we read the abstract and full-text, and excluded a further 58 papers. A final step involved reading the full text of the remaining 42 papers and excluding those which: (a) used non-spatial statistical techniques to cluster areas according to non-spatial agricultural or other characteristics; (b) modelled neighbourhood effects but did so without explicitly taking space into account; (c) studied the spatial allocation of agri-environmental subsidies in some aggregated form that included payments unrelated to EFA, such as the European Union's Rural Development Policy payments.

The final database included 39 papers and is given in Table A1 in the Appendix. To review the evidence on clustering, we used the full set of papers. To explore if spatial dependency is due to spatial autocorrelation or spatial heterogeneity, we used the subset of studies (nine) that employed the robust Lagrange Multiplier test (Anselin 1988) to test for the significance of spatial lag and/or spatial error. To conduct the qualitative analysis of the factors that influence the adoption or distribution of EFA, we used a sub-sample of the papers that used spatial statistical models (27 papers). To review the factors that have spillover effects, we used a different sub-sample of the database that included particular models that are able to provide these kinds of estimates, i.e. spatial Durbin models and spatial lag of X models (8 papers). For each paper in the database, we recorded the fields mentioned in Table 1 (bibliographic data are excluded from the table but were recorded). If a study analysed more than one type of EFA system or practice (e.g. integrated and organic farming), or studied a system or practice across places or crops, we recorded the findings separately. For example, for Früh-Müller et al. (2019) who built simultaneous autoregressive (SAR) models for Germany (national scale) and 12 German federal states, we recorded the results for all models separately, included significant and insignificant variables. The same for Raggi et al. (2015) who used separate fractional logit models with spatial lags for organic farming schemes, integrated production schemes and meadows and grazing payments – and all studies that built more than one model for different crops, system, practices, or areas.

Table 1. Fields recorded for each paper in the final database.

Field	Description
Case study: Country	Country studied or country for case study setting
Case study: Extent	International; National; Regional/ Local
Case study: Resolution	Region; Country; Municipality; Farm (etc.)
Practice(s) or type(s)	Type(s) of farming (e.g. organic) or practice(s) (e.g. no tillage)
System / crop(s)	Crop type(s) (e.g. vines) or farming system(s) (e.g. dairy cows)
Dependent variable(s)	Variable(s) analysed (e.g. adoption, rate of adoption)
Multi-temporal	Whether a longitudinal or multi-year study/ data study
Methods of analysis	All analytical methods of analysis (e.g. Moran's I, SLX)
Other variables examined	If relevant, all variables included in the statistical models
Spatial pattern(s): general	Findings regarding spatial patterning
Spatial effect by variable	If relevant, sign of spatial effect *by variable* (e.g. SDM)
Significant variables and signs	If relevant, significant variables and signs

5 Results

5.1 Case study characteristics

The majority of the studies (75%, Table 2) have been conducted in European (25) or North American countries (4), while 40% of the studies have been conducted in three countries: Italy (6), Great Britain (6), and USA (4). Furthermore, and relatedly, the vast majority of the studies refer to richer countries (Tables A2 and A3), as according to the World Bank lending group classification 33 studies refer to high-income economies (84%), and only 2 to lower-middle or low-income economies (5%). The scale of analysis is evenly split between national (22) and regional/local (18) case studies, with only one study having an international character (Zasada et al. 2018). This split is in turn reflected in the resolution of analysis (Table A4), whereby one third of the studies centre on farms (14), while the rest, which include both national and sub-national/regional case studies, focus on some kind of governance unit. Most studies focus on municipalities and/ or Local Administrative Units (an EU statistical unit), followed by counties (mainly in USA and England), and grid cells. 68% (28) of the case study foci reviewed are concerned with farming systems, the majority of which (60%) deal with organic farming. Six studies deal with various agri-environmental schemes, mainly EU Rural Development/ Common Agricultural Policy-related (Tables 3 and A5). Only 17% (7) deal with of particular practices or bundles of practices, such as conservation/no- tillage or fallow land. Notably, only 20% (8) of the studies have a multi-temporal perspective, with the majority (31) analysing data from a single year.

Table 2. Case study countries and World Bank classification, in alphabetical order.

Country	Count	World Bank region	World Bank lending groups
Bulgaria	1	Europe and Central Asia	Upper-middle income economies
China	2	East Asia and Pacific	Upper-middle income economies
Croatia	1	Europe and Central Asia	High-income economies
Czechia	1	Europe and Central Asia	High-income economies
Denmark	1	Europe and Central Asia	High-income economies
Ethiopia	1	Sub-Saharan Africa	Low-income economies
EU	1	Europe and Central Asia	High-income economies
Finland	1	Europe and Central Asia	High-income economies
France	3	Latin America and Caribbean	High-income economies
Germany	3	Europe and Central Asia	High-income economies
Honduras	1	Latin America and Caribbean	Lower-middle income economies
Ireland	2	Europe and Central Asia	High-income economies
Italy	6	Europe and Central Asia	High-income economies
Netherlands	1	Europe and Central Asia	High-income economies
New Zealand	1	East Asia and Pacific	High-income economies
Norway	1	Europe and Central Asia	High-income economies
Peru	1	Latin America and Caribbean	Upper-middle income economies
Taiwan	1	East Asia and Pacific	High-income economies
Great Britain	6	Europe and Central Asia	High-income economies
USA	4	North America	High-income economies

Table 3. Focus of analysis.

Focus	Count	Type of focus	Country
Low input farming	1	System	France
Best management practices for water	1	Bundle of practices	New Zealand
Conservation measures	1	Bundle of practices	Netherlands
Conservation tillage	1	Practice	Ethiopia
Environmentally Sensitive Areas payments for ecosystem services	1	Scheme	Scotland

EU agri-environmental schemes	4	Scheme	Italy; France; Bulgaria; Czech Republic
Fallow land	1	Practice	Peru
Fertiliser and pesticide reduction technologies	1	Bundle of practices	China
Green control	1	Bundle of practice	China
Natural Capital-related Rural development Funds	1	Scheme	EU
Conservation agriculture	1	System	Italy
No tillage	1	Practice	Italy
Integrated production	1	System	Italy
Organic farming	25	System	Multiple
Grand total	41		

5.2 Synthesis of findings

5.2.1 Evidence of clustering and type of clustering

95% (37) of the studies reviewed here report some kind of clustered spatial distribution of environmentally-friendly practices or farming systems (Table 4). Only 5% (two) studies report a random spatial distribution: Kazakova-Mateva (2020) for organic farming at the national scale in Bulgaria, and Boncinelli et al. (2017) for organic viticulture in Chianti, Italy.

Interestingly though, studies that attempt to disaggregate their findings by place, crop, farming intensity, or some other kind of conceptual or empirical schema provide some counter-evidence regarding the spatial clustering of EFA systems and practices. In addition to the two studies that report a random spatial distribution, 18% (7) of the 39 studies report that at least for some crop, in some place, administrative unit or scale, and farming organisation, the spatial distribution is random or dispersed. Thus, circa one quarter (23%, 9) of the studies reviewed here find a random spatial distribution for some element of EFA. Früh-Müller et al. (2019) find that agri-environmental payments are randomly distributed or even dispersed in several federal states of Germany, while for others and for Germany as a whole it is clustered. Zasada et al. (2018) in an EU-wide study report that one of the six ‘region types’ with high Natural Capital spending in agriculture is not spatially clustered, while the rest are. Van der Horst (2011) finds that in some areas the adoption of the Scottish ‘Environmentally Sensitive Area’ payments for ecosystem services scheme is not spatially clustered. Ilbery et al. (1999), Nyblom et al. (2003), Petit and Aubry (2014) find that while organic agriculture as a farming system might be spatially clustered, organic farming for particular types of production is not (organic grass and fodder enterprises and organic livestock enterprises for Ilbery et al. (1999); organic animal products other than pork, beef and/or milk production for Nyblom et al. (2003); sugarbeet for Petit and Aubry (2014). Finally, Ilbery and Maye (2011) report that within two counties in South East England the spatial distribution of organic farming is random. We note that the ‘non-clustered’ findings do not seem to be related to a country, type of dependent variable or study resolution, as can be seen in Table 4. We also want to highlight that six of the nine studies that report some type of non-clustered distribution refer to local and/or regional extent studies. Thus, one third (6 out of 18) of the local and/or regional studies find evidence of random or dispersed distribution of some type of environmentally-friendly agricultural system, practice or scheme.

Table 4. Spatial distribution of ecologically-friendly systems and practices. We do not include data on papers, country, dependent variable, resolution and extent for the studies which find clustered spatial distributions as they are too numerous to include here and plus they cover all the ranges of these characteristics.

Spatial distribution	**Count**	**Papers**	**Country**	**Dependent variable**	**Resolution**	**Extent**
Clustered	30	-	Multiple	Multiple	Multiple	Multiple
Clustered - dispersed by analysis unit/ place	1	Früh-Müller et al. (2019)	Germany	Agri-environmental payments/UAA	Municipality	Regional
Clustered - random by type of share of Natural Capital funding	1	Zasada et al. (2018)	EU	Presence of particular type of high Natural Capital spending agriculture	NUTS2/NUTS3	EU
Clustered - random by analysis unit/ place	1	Van der Horst (2011)	Scotland	Presence of scheme adoption	Farm	Local
Clustered - random by crop	3	Ilbery et al. (1999); Nyblom et al. (2003); Petit and Aubry (2014)	England and Wales; Finland; France	Location quotient of number of organic farms; adoption of organic farming; presence of organic farms	County; Farm; Farm	National; Local; Local
Clustered - random by scale	1	Ilbery & Maye (2011)	England and Wales	Qualitative finding	County	Regional
Random	2	Boncinelli et al (2017); Kazakova-Mateva (2020)	Italy; Bulgaria	Adoption of organic viticulture; number of beneficiaries	Farm; District	Local; National
Grand Total	39					

Furthermore, we explored studies that used a formal statistical test (the Robust Lagrange multiplier test) to differentiate between the drivers of clustering: spatial autocorrelation versus spatial heterogeneity. Table 5 below indicates that aside from Boncinelli et al. (2017) who did not find evidence of clustering *in toto*, two studies did not find evidence of spatial lag (i.e. spatial autocorrelation) regarding organic farming (Bartolini and Vergamini 2019) and green control measures (Li et al. 2018), both at the regional scale. This indicates that the clustering we see is not a result of neighbourhood effects but a result of spatial heterogeneity; i.e. there are variables not included in the models that likely affect the spatial distribution of organic farming or green control measures in Marche, Italy, and Zhejiang and Jiangsu, China (Marasteanu and Jaenicke 2016). Despite these exceptions, the majority of studies that do employ a formal statistical procedure to differentiate between spatial lag and spatial error do find evidence of neighbour or agglomeration effects (i.e. spatial autocorrelation).

Table 5. Break down of studies that formally differentiate between spatial lag and spatial error, using the Lagrange Multiplier test. +: positive sign; -: negative sign; n: no effect.

Author	**Spatial autocorrelation**	**Spatial heterogeneity**	**Resolution**	**Extent**
Bartolini & Vergamini (2019)	+ (integrated production); - (organic farming)	+ (organic farming); - (integrated farming)	municipality	regional
Bjørkhaug & Blekesaune (2013)	+ (organic farming)	+ (organic farming)	municipality	national
Boncinelli et al. (2017)	- (organic viticulture)	- (organic viticulture)	farmer	regional
Marasteanu and Jaenicke (2016)	+ (organic farming); + (organic crops); + (organic livestock)	+ (organic farming); + (organic crops); + (organic livestock)	county	national
Schmidtner et al. (2012)	+ (organic farming);	n (organic farming	county	national
Schmidtner et al. (2015)	+ (organic farming, county); + (organic farming, community)	- (organic farming, county); n (organic farming, community)	county; community	regional
Li et al. (2018)	- (green control measures)	+ (green control measures)	farmer	regional
Swinton (2002)	+ (fallow practice)	n (fallow practice)	farmer	regional
Taus et al. (2013)	+ (organic farming)	- (organic farming)	county	national

5.2.1 Variables that influence spatial dependence with a focus on the local/ regional scale

We recorded 297 different variables entered in models in the 27 studies that used some kind of formal spatial statistical test to determine if they influence the adoption of EFA. Of those, 64% (191) were found to be significant in at least one study. Space precludes a full presentation here, so we only focus on the 30 variables that have been entered in more than three studies (Table 6). We did the same for the 13 local and/or regional studies, and recorded 156 different variables entered in models. Of those, 58% (91) were found to be significant in at least one study. In Table 6 we focus on the 27 variables that have been entered in more than two studies.

We can make some more confident arguments for variables that have a relatively high ratio of positive/negative or negative/positive signs (Table 6). Farmer characteristics *Education* and *Agricultural Education* do seem to have clearly positive influence on EFA adoption or uptake. *Age* and *Gender* do not have a clear effect. *Gender* is worthy of attention as it has been entered in seven studies, and found significant in only two; out of which it was estimated to have a negative sign by Yu et al. (2021) and a positive sign in Boncinelli et al. (2017). *Family size* also does not have a clear effect, with only one study finding a positive association (Wollni and Andersson 2014), while two did not find a significant effect. *No of association memberships* was found to have positive effect by two studies, although it was not significant in another two.

Regarding farm or wider agriculture economic characteristics, *Subsidies*, *% of organic operations or UAA* and *Livestock units* were straightforwardly associated with adoption, positively for the former two and negatively for the latter. *Farm size* was included in 11 studies, and only found significant in three, while the signs seem to be distributed evenly, giving an unclear perspective. *Part-time occupiers*, *% of farms with livestock*, *% of arable and UAA* are all significant for the majority studies they were entered, although again the signs are distributed evenly. *Non-farm income* was significant and negative in only one of the four studies it was entered, while *% of agri-touristic farms* was positive in only one of three studies it was entered. *% of UAA in total area* was not found significant in any of the studies it was entered. Notably, *Land capacity* was significant in only three out of the eight studies it was entered.

In terms of the built, social and natural environment, *Population density*, *% or Number of urban areas* and *Plain (binary)* (whether the farm is in a plain or not) showed a clear association with adoption or uptake of environmentally-friendly agriculture. Less strong associations were evident for *% of grassland* and *Precipitation* which both showed a positive association. *Nature conservation areas* (% or binary) and *Amenities* (%) were significant in the majority of the study models they were entered in, although the signs are again conflicting, indicating a crop, place, practice or system type effect. *Distance to the city*, *Mountain (binary or %)*, *% of water protection areas* are not significant in the majority of studies they were entered, although the low numbers (5-4) do not allow for safe elimination, especially considering *Mountain (binary or %)* and *Distance to the city* were significant in one study each. *Distance to demonstration farm* was not found significant in any of the studies it was entered.

If we narrow down our sample and consider only local or regional level studies, naturally, the number of studies is smaller, so we can be less confident in our conclusions. However the findings do not differ greatly (Table 6). Notably, in contrast to the global sample, for the local and regional scale, *Part-Time occupiers* seem to only have negative effects, while *Farm size* only positive. Furthermore, we can more or less confidently argue that *Education*, *Agricultural education*, *Subsidies* and *Operations or UAA that is organic* have a positive effect, while increased *Land capacity*, *Population density* and *Urban areas* have negative effects. *Age*, *Distance to the city*, *% of Water protection areas* and *Precipitation* seem to rarely be significant when included in models, indicating that they do not always play a role in the adoption or uptake of EFA at the local and regional scales.

Table 6. Variables that are thought to affect adoption and were entered in more than three studies. Some studies built more than one model; in these cases all significant model variables and signs were recorded separately for each model. Numbers in parentheses refer to local and/or regional studies.

Variable	**Studies**	**Significant in No of studies**	**Significant in No of models**	**+ sign**	**- sign**
Education	12 (8)	6 (5)	8 (7)	7 (6)	1 (1)
Age	12 (7)	5 (2)	5 (2)	2 (1)	3 (1)
Farm size	11 (6)	3 (2)	5 (2)	2 (2)	3 (0)
Nature conservation areas	10 (4)	8 (3)	25 (11)	19 (7)	6 (4)
Land capacity (soil)	8 (5)	3 (2)	8 (7)	1 (1)	7 (6)
Population density	8 (2)	7 (2)	12 (5)	2 (0)	10 (5)
Gender (male)	7 (4)	2 (2)	2 (2)	1 (1)	1 (1)
Urban areas, % or No.	6 (2)	3 (1)	8 (1)	1 (1)	7 (0)
Livestock units, per ha or farm	5 (3)	5 (3)	11 (7)	0 (0)	11 (7)
Arable, % of	5 (3)	4 (3)	7 (6)	2 (1)	5 (5)
Agri-touristic farms, % or binary	5 (1)	3 (1)	4 (2)	4 (2)	0 (0)
UAA	5 (2)	3 (1)	3 (1)	1 (0)	2 (1)
Distance to the city	5 (4)	1 (1)	2 (2)	2 (2)	0 (0)
Part-time occupiers, % or binary	4 (2)	4 (2)	4 (2)	2 (0)	2 (2)
Agricultural education	4 (3)	3 (2)	4 (3)	4 (3)	0 (0)
Association memberships, No	4 (3)	2 (2)	2 (2)	2 (2)	0 (0)
Non-farm income, binary or $	4 (3)	1 (1)	1 (1)	0 (0)	1 (1)
Mountain, binary or %	4 (1)	1 (0)	1 (0)	1 (0)	0 (0)
Water protection areas, %	4 (2)	0 (0)	0 (0)	0 (0)	0 (0)
Farms with livestock, %	3 (2)	3 (2)	6 (3)	3 (2)	3 (1)
Amenities, % or binary	3 (0)	3 (0)	3 (0)	2 (0)	1 (0)
Progressive voters, %	3 (1)	2 (1)	5 (2)	5 (2)	0 (0)
Organic operations or UAA, %	3 (1)	2 (1)	5 (4)	5 (4)	0 (0)
Plain, binary	3 (2)	2 (1)	3 (2)	0 (0)	3 (2)
Subsidy, $ or binary	3 (3)	2 (2)	3 (3)	3 (3)	0 (0)
Grassland, %	3 (2)	1 (1)	11 (11)	11 (11)	0 (0)
Precipitation	3 (2)	1 (0)	1 (0)	1 (0)	0 (0)
Family size	3 (2)	1 (1)	1 (1)	1 (1)	0 (0)
UAA in total area, %	3 (1)	0 (0)	0 (0)	0 (0)	0 (0)
Distance to demonstration farm	3 (2)	0 (0)	0 (0)	0 (0)	0 (0)

Training our focus on those variables that appear to show contradictory signs allows for a deeper interrogation of where those variables influence the spatial distribution of EFA (Tables 7 and 8). Starting with *Education*, while as mentioned above the overwhelming finding from the studies is that while it increases the chances of adoption or uptake for different systems and practices, for labour-intensive fertiliser and pesticide reduction practices it has the opposite effect (Yu et al. 2021). *Age* appears to have a positive effect for organic farming at the local scale in the Honduras (Wollni and Andersson

2014) and at the national scale in the USA (Kuo and Peters 2017), and negative for conservation measures in the Netherlands (Vroege et al. 2020), organic viticulture in Chianti, Italy (Boncinelli et al. 2017), and organic dairy in Ireland (Läpple & Kelley 2015). Importantly, *Age* is not significant for seven studies, including Tessema et al. (2016) for conservation tillage at the regional scale in Ethiopia, organic farming and EU AES uptake in Italy at the regional scale (Raggi et al. 2015; Boncinelli et al. 2016; Bartolini and Vergamini 2019; Bonfiglio and Arzeni 2019), best management practices at the regional scale in New Zealand (Yang and Sharp 2017), and organic farming at the national scale in the USA (Taus et al. 2013). *Gender* was entered in seven studies but was only significant in two: male farmers were more likely to adopt organic viticulture in Chianti, Italy (Boncinelli et al. 2017), and female farmers in relation to green control measures adoption in Shandong and Henan, China (Yu et al. 2021).

Farm size has a negative sign for organic agriculture in England (Gabriel et al. 2009) and USA (Taus et al. 2013) and positive for organic farming and integrated production in a regional scale study in Tuscany, Italy (Bartolini and Vergamini 2019). *Arable (%)* is negative for the uptake of integrated production in Tuscani (Bartolini and Vergamini 2019), but not in Emilia-Romagna (Raggi et al. 2015), where it is also negative for AES (all) and AES for meadows and grazing. Furthermore *Arable (%)* is positive for AES for habitat, but not for all the other types of AES studied (all, water, bird) in Scotland (Yang et al. 2014). Being a *Part-time occupier*, or the % of part-time occupiers in an area, is positive for the participation in organic farming AES in Tuscany, Italy (Boncinelli et al. 2016), and only for AES related to water in Scotland, where it is insignificant for all other AES studied (habitat, bird, and all) (Yang et al. 2014). It is negative for the adoption of organic viticulture in Chianti, Italy (Boncinelli et al. 2017) and integrated production but insignificant for organic farming in Emilia-Romagna, Italy (Raggi et al. 2015). *% of farm with livestock* is one of the most contradictory variables studied: it is positive for high natural capital spending regions with high natural value farmland with smaller farm and livestock grassland farming but not for regions with highly intensive agriculture with high population density at the EU scale (Zasada et al. 2018); it is positive for AES for meadows and grazing but negative for AES for integrated production in Emilia-Romagna in Italy (Raggi et al. 2015), but positive for integrated production in Tuscany, Italy (Bartolini and Vergamini 2019).

Nature conservation areas have a positive effect in AES uptake at the national scale and in five of the 12 federal states in Germany; organic farming and organically farmed crops but negative for organic livestock in USA (Marasteanu and Jaenicke 2016); organically farmed vegetable crops, viticulture and aromatic and medicinal plants but negative for organically farmed annual crops and temporary crops in France (Allaire et al. 2015); AES for meadows and grazing but negative for AES for organic farming and integrated production (Raggi et al. 2015); and for AES payments in total, AES % payments, AES % habitat payments; AES water payments; AES bird payments (17); AES % bird payments but neutral for AES habitat payments, and AES % water payments (Yang et al. 2014). *Population density* is positive for the presence of some types of high natural capital spending agriculture as categorised by Zasada et al. (2018) and negative for others; positive for organic farming at the national scale in Norway (Bjørkhaug and Blekesaune 2013), and negative for organic farming in AES schemes (all, organic and integrated production) uptake in Emilia-Romagna, Italy (Raggi et al. 2015) and Bavaria and Baden-Württemberg, Germany (Schmidtner et al. 2015). It is negative for conservation measures in the Netherlands (Vroege et al. 2020). *Urban areas* are only positive for organic farming in Marche, Italy (Bonfiglio and Arzeni 2019); negative for all types of organic farming at the national scale in the USA (Marasteanu and Jaenicke 2016), and AES payments, AES water payments, AES water % payments, AES bird payments, but insignificant for AES % payments, AES habitat payments and % payments. In the USA, two studies show contradictory results regarding the presence of natural or landscape *Amenities*: Kuo and Peters (2017) find a positive result, while Marasteanu and Jaenicke (2016) find a negative result for all organic operations (including agriculture and handling), but insignificant effects for organic crops and organic livestock. Vroege et al. (2020) also found a positive relationship of *Amenities* with the adoption of conservation measures in the Netherlands.

Focusing our attention on studies that build different models for exploring differences by crop, EFA system, type of practice and place (Table 8), we can see the same information from a different perspective. The different signs between organic crops and livestock in the USA, integrated farming and meadows and grazing schemes in France, labour, capital and skill intensive green control practices in China, or federal states in Germany underscore how highly contextual many factors of adoption are.

Table 7. A focus on particular variables. Numbers in parentheses refer to studies as numbered in Table A1. OF: organic farming; IP: integrated production. RT: 'Region Type' is a dependent variable from Zasada et al. (2018) which refers to region-types with high Natural Capital spending in agriculture.

Variable	+ sign studies	- sign studies
Education	Green control measures (36); OF (35); capital intensive low-input technologies (30); high-skilled low-input technologies (30); OF (26); organic viticulture (27); conservation tillage (19)	Labour-intensive low-input technologies (30)
Farm size	OF (29); IP (29)	OF (15); OF presence (6); OF density (6)
Nature conservation areas	AES, Germany and five (out of 12) federal states (32); OF (23); OF crops (23); OF vegetable crops, viticulture, aromatic, medicinal plants (22); AES meadows and grazing (20); AES payments (17); AES % (17); AES habitat % (17); AES water payments (17); AES bird payments (17); AES bird % (17)	OF (29); IP (29); OF livestock (23); OF annual crops and temporary grassland (22); AES OF (20); AES IP (20)
Age	OF (26); OF (16)	Conservation measures (37); organic viticulture (27); OF dairy (21)
Population density	RT 2 (33); OF (14)	Conservation measures (37); - RT 3 (33); AES all (20); AES IP (20); OF (20); OF counties (11); OF counties (11)
Urban areas, % or No.	OF (35)	OF all (23); OF crop (23); OF livestock (23); AES payments (17); AES Water payments (17); AES Water % (17); AES Bird payments (17)
Gender	Organic viticulture (27)	Green control measures (36)
Arable, %	AES IP (29); AES habitat (17)	OF (35); OF (29); AES all (20), IP (20); AES meadows and grazing (20)
Part-time occupiers	OF (25); AES water (17)	Organic viticulture (27); IP (20)
Farms with livestock, %	RT 2 (33); IP (29); AES meadows and grazing (20)	inclusion in High Natural Capital areas (33); RT 6 (33); AES IP (20)
Amenities	Conservation measures (37); OF (26)	OF all (23)

Table 8. Selected variables that appear to have both positive and negative influence on EFA adoption from single studies, showing differences by crop, EFA system, type of practice and place. RT: Region Type is a dependent variable from Zasada et al. (2018) which refers to region-types with high Natural Capital spending in agriculture.

Variable	**Significant in No of studies**	**+ Signs**	**- Signs**	**Studies and systems, practices, places, etc**
Nature conservation areas	7	18	6	+ organic all, + organic crops, - organic livestock (32); - annual crops and temporary grassland, + field vegetable crops, viticulture, and aromatic plants (22); - integrated farming, + meadows and grazing, - organic farming (20)
Livestock farms, %	3	3	3	- inclusion, + Region Type 2, - Region Type 6 (33); - integrated farming, + meadows and grazing (20)
Population density	3	1	7	- inclusion, + RT2, - RT3 (33)
Arable, %	3	2	4	- organic farming, + integrated farming (29)
Least favourable areas	1	2	2	- inclusion, + RT1, + RT2, - RT5 (33)
Holdings with <5 ha UAA, %	1	1	3	- inclusion, - RT3, - RT4, + RT5 (33)
Education	1	2	1	- labour intensive, + capital intensive, + highskilled (30)
Land values	1	2	1	+ organic spatial, + organic crops, - organic livestock (23)
Commute time, average	1	1	2	+ organic, - organic crop, - organic livestock (23)
Farms with forest, %	1	2	1	+ all AES, - integrated farming, + organic farming (20)
Beneficiaries for RDP1 measures type 3, No.	1	2	1	+ permanent grassland, - vegetable crops, viticulture, and aromatic plants, + permanent grassland, annual crops, temporary grass (22)
Beneficiaries for RDP1 measures type 4, No.	1	2	1	+ permanent grassland, + annual crops and temporary grassland, - market gardening and arboriculture (22)
Double season rice/crop	1	1	1	+ labour intensive, - high skilled (30)
Gross Value Added primary sector	1	1	1	+ RT3, - RT5 (33)
Total retail sales	1	1	1	- organic crop, + organic livestock (23)
Unified prevention and control	1	1	1	+ capital intensive, - high skilled (30)
Land capacity	1	1	0	- Germany, - Baden-Wurttemberg, - North Rhine-Westphalia, - Saarland, + Schleswig-Holstein (32)

5.2.1 Variables with a spatial function

21% (8) studies use spatial Durbin or spatial lag of X (SLX) models that can identify the influence of the spatial lags of particular independent variables on the neighbouring units of analysis. 46 variables were found to have significant spillover effects on neighbouring farmers or administrative units, out of 60 that were significant (in direct and spillover effects) in the models applied by the eight studies (76%). Only 15% (5) were significant for more than two studies (Table 9). The number of studies and total models are not high enough to provide robust indications of positive or negative spillover effects for most variables. Nevertheless, we can make the following observations.

Regarding the three most commonly studied farmer characteristics, only *Age* seems to have nearly consistent significant spillover effects (4 out 5 studies), although the sign of this effect is not consistent, with three studies showing a negative sign, and one positive (Wollni and Andersson 2014). *Gender* has significant spillover effects in 50% of the studies, and again the results are contradictory, with Yu et al. (2021) finding that being a female farmer positively affects the adoption of green control techniques by neighbours at a regional scale in China. Finally, *Education* is only significant in one out of six studies it was entered as a control variable (Yu et al. 2021), and it has a positive spillover effect. Farmer's *Risk attitude* entered in only two studies was found to have significant spillover effects in both studies, and consistent signs (Läpple and Kelley 2015; Yu et al. 2021).

Farm structure characteristics *No. of workers* and *Livestock units* were found to have significant spillover effects in both studies they were entered. *Livestock units* has consistent negative signs, while *No of workers* does not. From the only study that has an administrative unit resolution (Marasteanu and Jaenicke 2016) we can draw some conclusions in relation to the hypothesis that different crops have different spatial patterns of adoption. By employing a modelling approach that separately models organic producers *in toto*, organic crop producers, and organic livestock producers, the authors show different or non-existent spillover effects for the variables *Land values*, *Total retail sales*, *Average farm income*, *No. of operations participating in crop insurance,* while *% of progressive/ environmentally-minded voters* and *Average commute time* have consistently positive and negative spillover effects respectively.

6 Discussion

Below we discuss our findings in light of the literature on the geographical distribution of ecologically-friendly agriculture, and provide some tentative insights for policy makers and designers. We first explore the methodological implications of the studies in our corpus, and then discuss the studies' findings in detail.

Table 9. Spatial spillover effects of 15 variables included in spatial Durbin or SLX models. Variables shown are either included in models by multiple authors, or have been found to be significant by more than two studies. Some studies build more than one model, and in these cases we included all models for every study.

Variable	No of authors	Significant in No of studies	Significant in No of models	+ sign	- sign
Age of farmer or household head	5	4	4	1	3
% of progressive/ environmentally-minded voters	1	1	3	3	0
Land values	1	1	3	2	1
Average commute time (county)	1	1	3	0	3
Gender (male)	4	2	2	1	1
Risk attitude (Likert)	2	2	2	1	1
No. of workers	2	2	2	1	1
Livestock units per ha or per farm	2	2	2	0	2
Nature conservation areas	1	1	2	1	1
Total retail sales (county)	1	1	2	1	1
Average farm income (county)	1	1	2	0	2
No. of operations participating in crop insurance (county)	1	1	2	0	2
Knows other organic farmers (binary)	2	1	1	1	0
Education of farmer or household head	6	1	1	1	0
Amenities	2	1	1	0	1

6.1 Methodological bias and implications

The majority of studies refer to organic farming, leaving space for exploration of other ecologically-friendly farming systems (Table 3), which might not spatially behave in the same way organic farming does. In this respect, the few studies that explore different farming systems in the same space, such as Raggi et al. (2015) and Bartolini and Vergamini (2019) on integrated and organic farming, are particularly important, as we begin to see differences in the spatial patterns of adoption between farming systems and in the factors that influence these patterns. Considering the increasing plurality of alternative agricultural systems globally, such an exploration could yield novel insights and inform relevant and nascent policy initiatives such as regenerative farming (Rhodes 2017; LaCanne and Lundgren 2018), agro-ecology (European Committee of the Regions 2021) or degrowth (Amate and De Molina 2013; Gomiero 2018). Especially at the international and national levels, evidence of clustering (or randomness and dispersal) could lead to different targeting and information dissemination policies.

In addition, organic farming bias leads to a paucity of studies on particular practices or bundles of practices like integrated pest or water management practices. Our findings (see below) suggest that different practices have their own spatial distribution and patterns of adoption, often with regional and or local characteristics, and aggregated analysis might provide conflicting results (Mozzato et al. 2018). Thus more research is needed on spatial patterns in the adoption of particular practices. Considering that a large percentage of farmers might not follow a particular farming system as a whole, but rather use and explore a variety of practices and bundles of practices, deeper knowledge on this front could inform option-based programmes such as EU agri-environmental schemes or England's Countryside Stewardship. Particularly for regional concerns, such an individual option analysis could be feasible and 'would be more suitable, accounting for the regional diversity in land characteristics and the specifics of option eligibility' (Yang et al. 2014, p. 113).

We also found that the majority of the studies have been conducted in Western countries and high-middle to higher income economies. The results of our review suggest that there is a significant lacuna regarding studies in what is commonly referred to as the Global South, i.e. poorer countries in South East Asia, Latin America, Northern and Southern Africa, and the Middle East. This methodological "Westerness" could signal a potential bias. We have to consider Malek et al. (2019) and Mozzato et al. (2018) who found that different variables control for the distribution of organic farming in poorer regions compared to richer regions in the Global North. Furthermore, considering the different cultural, political and economic practices present in non-Western, non-European, parts of the world, and how these are reflected in different adoption patterns, extending this sub-discipline's field of vision to other parts of the world, could yield novel insights (e.g. Nga and Drakou 2021), or associations that have not been unearthed yet.

6.2 Evidence of spatial clustering

In accordance to the literature, our findings suggest that EFA systems and practices often display some kind of spatial clustering; predominantly at the national scale, EFA systems and practices seem to be spatially concentrated. This is particularly true for organic farming, for which most of the evidence is collected. Nevertheless, a more detailed analysis indicates that this seeming universality of spatial clustering might not be as uniform as it initially seems. Aside from the two studies that found no evidence for spatial clustering for organic farming in Bulgaria (Kazakova-Mateva 2020) and organic viticulture in Chianti, Italy (Boncinelli et al. 2017), a host of studies found evidence of spatial randomness and dispersal if EFA is disaggregated by place, crop, system, scheme or practice. This is particularly true for studies at the local and/or regional scale, where circa one third of the studies found evidence of non-clustered spatial distribution. This finding challenges the often held belief (Boncinelli et al. 2017) that EFA systems and practices are by definition clustered, and indicates that more research is required to disentangle the complex processes driving EFA adoption and uptake. Moreover, in terms of practical implications, it points to the limits of information- and/ or network-based attempts at EFA implementation, which are a staple of policy design worldwide.

On the other hand, the limited number of studies (9) that specifically tested for spatial autocorrelation versus heterogeneity in explaining *documented* spatial dependency provide alternative argumentation. Our findings show that documented spatial dependency is well captured by spatial lag models, indicating that spillover effects are prevalent in EFA systems and practices that are spatially clustered. 'Neighbourhoods', be they comprised of farmers or administrative units, are significant units of influence in the adoption or uptake of EFA. Thus, while spatial clustering cannot be argued to be a universal phenomenon regarding EFA systems and practices, where it occurs, it is largely influenced by neighbourhood or agglomeration ('economies of scale') spillover effects. A caveat may be added to this statement: often targeted AES and other schemes usually select areas with specific natural and agricultural characteristics, thus (wrongly) amplifying a neighbourhood spatial lag effect.

Naturally, the robust Lagrange multiplier test that studies use to differentiate between spatial lag and error cannot test for accounted for spatial heterogeneity, i.e. if spatial heterogeneity is captured by variables included in the statistical model, it cannot be detected. This does not mean that spatial heterogeneity is absent, or insignificant. As numerous studies show and the section below summarises, spatial heterogeneity is often a decisive element in the spatial distribution of EFA systems and practices.

6.3 Variables that influence adoption

27 studies used some kind of formal statistical test to determine which factors influence the adoption or uptake of EFA systems and practices. Almost 300 different variables were used, the majority of which was only used by one study, indicating that the research is still in its exploratory phase, testing a wide variety of hypotheses in new places, under new conditions or frameworks. 64% (191) of variables were found to be significant by more than one study, limiting our ability to discuss them in full here, a limitation compounded by the fact that 77% (148) of those variables were only found to be significant by one study. However, this is a limitation we were willing to accept in order to ensure we only reviewed studies that used spatial statistical models that avoid some of the limitations inherent in models and reviews that do not take spatial dependency into account. Naturally, similar limitations hold for the regional and local subset of studies, slightly stronger for the subset we used to identify factors with spatial spillover effects (eight studies).

Nevertheless, we can make some observations and offer some ideas for further study. Firstly, and responding to the fragmentation of the research strategies as evidenced by the large number of variables used in spatial statistical modelling, conceptual schemata such as the one offered by Liu et al. (2018) can be invaluable in identifying key priorities for research. Liu et al. (2018), by devising a framework for best management practices adoption highlight both micro and macro scales of influence, although spatial dependency is only included as spatial heterogeneity in their framework.

There are series of variables for which we can make safe remarks. Only five variables seem to have more-or-less straightforward and consistent significance and signs. *Livestock units* and *Plain* (binary) have negative influence, while *Agri-tourism*, *Subsidies* and *Education* (including *Agricultural education*) have a positive influence. This finding is in accordance with recent reviews (Liu et al. 2018; Mozzato et al. 2018) and research (e.g. Guo et al. 2021), with the exception of *Agri-tourism*, whose positive influence on EFA adoption and uptake seems to have escaped attention as an important factor – although Western bias might be influencing this finding. The relative concentration of EFA in less agriculturally productive areas is reflected in the significance and sign of the *Plain* factor, indicating the influence of spatial heterogeneity on spatial patterns of EFA adoption and uptake (see also variable *Mountain* which however does not seem to have such a straightforward reading). Of these variables, *Livestock units* seems to have significant local spillover effects in two widely different contexts, implying that richer farmers in Ethiopia (Tessema et al. 2016) or more intensive farms in Ireland (Läpple and Kelley 2015) negatively impact the adoption probabilities of neighbouring farmers. On the other hand, counterintuitively, *Education*, while significant for farmers themselves, does not seem to have local spillover effects as we would expect from an innovation or information diffusion framework (Hägerstrand 1967 [1953]). For three variables we can make more or less confident assumptions that they do not influence adoption or uptake of EFA, including lack of spatial spillover effects: *% UAA in total area*, *Distance to demonstration farm* and *Water protection areas*. These are important findings, as they allow us to begin to understand that a series of factors that have been repeatedly tested seem to play little role in the adoption or uptake of EFA systems and practices at the national scale.

Exploring national versus regional/local characteristics in variable significance, we can see *Gender*, *Association memberships*, *Subsidies*, and *Family size* only seem to be significant at a local and/or regional scale, while *Amenities* seems to only be significant at the national scale. This finding is bolstered by the results of Früh-Müller et al. (2019) who employed different models for the national scale and 12 federal states in Germany, and found that different factors are significant between and across scales. The difference between local/regional and national models adds scale as a vector of difference along with large scale/ continental difference (Mozzato et al. 2018) or the macro ("watershed, regional or national") versus micro (farm) scale of Liu et al. (2018). Interestingly, *Gender*, *Association membership* and *Amenities* also display spatial spillover effects, adding another vector of micro (*sensu* Liu et al. 2018) or telecoupling influences (Zimmerer et al. 2018), as both farmer characteristics and landscape characteristics can influence local/ regional adoption or uptake of EFA systems and practices.

Relatedly, theoretical accounts that stress the relationality of agricultural space, as well as studies that focus on different areas or scales point to a hypothesis that there might be different variables controlling the spatial distribution of EFA as well as the prevalence or adoption of EFA across different places/ geographical/ administrative units, even considering nested scales such as counties in a state or municipalities within a county (Schmidtner et al. 2015; Früh-Müller et al. 2019). Thus, while as Mozzato et al. (2018) argue there might be some large-scale geographical perspectives that hold true for EFA, our findings point to within country differences that their schema cannot interpret. This finding is supported by studies which look at the non-stationarity of the relationship between EFA adoption and its determinants. Taus et al. (2013) who found for example the farm size has a negative association with organic farming adoption in Maine, New Hampshire, Massachusetts, central California and in the Southeast region in Georgia and Florida, but positive in the Northeast and the West (USA). Früh-Müller et al. (2019) found that organic farming is not clustered in all German federal states, and its spatial distribution is determined by different variables in every state. In this respect, studying the non-stationarity of factors influencing the distribution of EFA is an avenue worth taking, following the work of Taus et al. (2013) who used Geographically Weighted Regression, or Ilberry and Maye (2011, p. 34) who used a qualitative approach ('whole chain approach') that relies on supply chain diagrams to 'map the supply chain geography of individual organic businesses and to understand why, or why not, spatial clustering was occurring'.

From our perspective, the main interest though lies in the factors that are found to be significant by a number of studies, but appear to have contradictory influences on adoption or uptake of EFA systems and practices between and within studies, systems, practices and scales. Here, the highly contextual nature of EFA systems and practices becomes apparent, at least in the terms it is understood up to now. For example, close to our work here, innovation diffusion (*sensu* Hägerstrand 1967[1953]) explanations (e.g. Van der Horst 2011), or agglomeration economies understanding might be applicable in some cases, nevertheless, their usefulness in case will – for now – have to be proven on a case by case basis.

So, in the question of which factors are the most important for furthering the adoption or uptake of EFA systems and practices, the answer for now can only be: it depends. Thus, future work should focus on disentangling the complex relationship between farming systems, practices and systems of practices, with spatial distribution of EFA uptake and adoption. Conceptual and empirical frameworks that meaningfully disaggregate/aggregate EFA systems and practices are required to accomplish this difficult task (see e.g. Rega et al. 2018), as current overviews – like ours – often suffer from the caveat of bundling diverse practices, bundles of practices and land uses together (e.g. Liu et al. 2018; Mozzato et al. 2018; Zimmerer et al. 2018), without really going into the details of every practice and system. The conflation of systems and practices is particularly problematic as the adoption of EFA systems like organic farming is often the result of tangled economic, cultural, and personal choices in a way that the adoption of single practices is not, especially in areas with small farms, where the choice is often unrelated to economic factors. Finally, we believe scholars should be willing to accept a multi-causal understanding of spatial patterns of adoption (and perhaps adoption in general), identifying causes and drivers of adoption and unpacking how, when, where and why certain EFA systems and practices may be valued. One way to achieve this could be through interdisciplinary place-based research, where historiography, sociology and anthropology of the rural, agronomy and agricultural economics, as well as their spatial cognate disciplines, could engage in thick studies of particular regions or localities through a plurality of lenses (Pascual et al. 2021).

7 Conclusion and implications

We conducted the first global meta-analysis of the spatial distribution of EFA systems and practices, as well as of the factors that influence it as estimated using spatial models only. Our findings are novel and we summarise them here. Geographical and farming system biases in the literature hinder global and regional/local understanding. Studies such as Malek et al. (2019) are part of the way forward regarding the geographical aspect, although farming system biases are prominent and still unsolved. Spatial clustering is indeed a feature of agricultural systems and practices, although perhaps not as universal as commonly presented. Especially at the local and regional scales, the jury is still out regarding when, where and under which conditions we can expect an ecologically-friendly farming system or practice to display clustered spatial distribution. Where it occurs, spatial dependency is almost always a function of spatial autocorrelation, i.e. neighbour spillover effects certainly play a prominent role where and when spatial clustering of EFA systems and practices occurs. Similarly to spatial clustering, for the factors that influence adoption as estimated using only spatial models, there are only a few factors consistently significant or insignificant, and even fewer that have consistent signs. There are differences across and within systems, practices, scales and places, and more focused, interdisciplinary and placed-based research is required. There is an important distinction between local/regional and national spatial patterns and processes of adoption, evident in the differences between the different factors significant for national and local/regional scale models, as well as by the numerous factors that appear to have significant local-regional (farm to circa 100 km) spillover effects.

The lack of clear findings (e.g. "organic farming is spatially clustered because of innovation diffusion effects") should not deter us from drawing some tentative implications for policy and practice. Considering that the value (economic or otherwise) of many ecosystem services and public goods can be maximised from the clustered distribution of EFA systems and practices (Sutherland et al. 2012), more effort should be spent on designing policies that drive neighbouring farmers' adoption. However, in designing these policies care should be taken to account for the fact that for variety of economic and/or market geography reasons, this clustered pattern of EFA adoption might not be possible. In these cases, organisationally and geographically anarchic (lack of) coordination regarding EFA, with different 'approaches, conceptualisations, methodologies, data, etc. employed to operationalise (supposedly) the same concept' comes with a 'price of anarchy' (Bormpoudakis and Tzanopoulos 2019) in terms of ecosystem services and public goods.

The divergent findings from studies at the national versus local/regional scale are also significant on policy terms. Considering that most AES programs or subsidy policies are coordinated at the national scale, care should be taken by policy makers to evaluate their spatial and other effects at subnational scales. To not do so would risk misunderstanding why certain policies are adopted (or not), and misidentifying the factors that affect adoption patterns.

In terms of the LIFT project's remaining work, the findings of this study are especially relevant for the design of the hypothetical landscape of task 4.1., which will be used for assessing the ecosystem services and public goods of EFA systems and practices at the territorial scale in task 4.3. As a result of the findings of this report, we have devised a methodology that does not assume a certain level of clustering of EFA systems and practices in the case study territories. Instead we designed a methodology that creates a set of hypothetical landscapes with different levels of clustering for each case study territory.

8 Acknowledgements

We thank all scholars whose work we cite and summarise here; our findings and discussion in no way limit the importance of their research. We thank our colleagues in the LIFT project for invaluable input at all stages of this research, and especially Kato Van Ruymbeke and Wolfgang Britz for incisive and helpful comments. All shortcomings remain of course ours.

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10 Appendix

Full search term used in Scopus

> *(TITLE-ABS-KEY (spatial* OR "neighbo*" OR "network ana*" OR "Network Ana*" OR "Neighborhood effect" OR "neighborhood effect" OR "Neighbourhood effect" OR "neighbourhood effect")) AND (TITLE-ABS-KEY ("organic farm*" OR "organic agri*" OR "agri-envi*" OR agrienvi* OR "sustaina* farm*" OR "sustaina* agri*" OR "sustaina* practi*" OR "alternativ* farm*" OR "alternativ* agri*" OR "alternativ* crop*" OR "agrobiodiversi*" OR "agro-biodivers*" OR "rural development" OR "management practice*" OR "best management practice*" OR "green control techniques" OR "farming practic*" OR "integrated farm*" OR "integrated agricul*")) AND (TITLE-ABS-KEY ("agri*" OR "farm*" OR "devel*")) AND (LIMIT-TO (SRCTYPE , "j")) AND (EXCLUDE (SUBJAREA , "BIOC") OR EXCLUDE (SUBJAREA , "MEDI") OR EXCLUDE (SUBJAREA , "ARTS") OR EXCLUDE (SUBJAREA , "IMMU") OR EXCLUDE (SUBJAREA , "CHEM") OR EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "NEUR") OR EXCLUDE (SUBJAREA , "NURS") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE (SUBJAREA , "DENT"))*

Table A1. List of papers included in the final database, ranked by year of publication.

No	Authors	Publication year	Source
1	Cudjoe & Rees	1992	Tijdschrift voor Economische en Sociale Geografie
2	Ilbery et al.	1999	Tijdschrift voor Economische en Sociale Geografie
3	Swinton	2002	Agricultural Economics
4	Nyblom et al.	2003	Social Networks
5	Frederiksen & Langer	2004	Tijdschrift voor Economische en Sociale Geografie
6	Gabriel et al.	2009	Journal of Applied Ecology
7	Lewis et al.	2011	Land Economics
8	Ilbery & Maye	2011	Area
9	van der Horst	2011	Applied Geography
10	Schmidtner et al	2012	European Review of Agricultural Economics
11	Schmidtner et al	2015	German Journal of Agricultural Economics
12	Teillard et al	2012	Agriculture, Ecosystems and Environment
13	Lapple and Cullinan	2012	Irish Geography
14	Bjørkhauga & Blekesaune	2013	Geoforum
15	Taus et al	2013	The Professional Geographer
16	Wollni & Andersson	2014	Ecological Economics
17	Yang et al	2014	Journal of Environmental Management
18	Petit and Aubry	2014	Agroecology and Sustainable Food Systems
19	Tessema et al	2016	African Journal of Agricultural and Resource Economics
20	Raggi et al	2015	Land Use Policy
21	Läpple & Kelley	2015	European Review of Agricultural Economics
22	Allaire et al	2015	Ecological Indicators
23	Marasteanu & Jaenicke	2016	Agricultural and Resource Economics Review
24	Marandola et al	2016	Agricultural and Food Economics
25	Boncinelli et al	2016	Renewable Agriculture and Food Systems
26	Kuo and Peters	2017	Agroecology and Sustainable Food Systems
27	Boncinelli et al	2017	New Medit
28	Yang & Sharp	2017	Environmental Management
29	Bartolini & Vergamini	2019	Sustainability
30	Li et al	2018	Sustainability
31	Hrabák & Konečný	2018	Norwegian Journal of Geography
32	Früh-Müller et al	2019	Land Use Policy
33	Zasada et al.	2019	Land Use Policy
34	Lu and Cheng	2019	Sustainability
35	Bonfiglio & Arzeni	2019	Bio-based and Applied Economics
36	Yu et al	2021	Agroecology and Sustainable Food Systems
37	Vroege et al	2020	Land Use Policy
38	Blace et al	2020	Land Use Policy
39	Kazakova-Mateva	2020	Bulgarian Journal of Agricultural Science

Table A10. Case study countries tallied by World Bank country group.

World Bank Country group	**Count**
East Asia and Pacific	4
Europe and Central Asia	25
Latin America and Caribbean	5
North America	4
Sub-Saharan Africa	1
Grand Total	39

Table A11. Case studies countries tallied by World Bank lending group.

World Bank Lending group	**Count**
High-income economies	33
Lower-middle income economies	1
Low-income economies	1
Upper-middle income economies	4
Grand Total	39

Table A4. Resolution of analysis.

Resolution	Count
Farm	14
County (USA and/or England)	9
Municipality or Local Administrative Units (LAU2)	7
Grid cell (Italy)	2
NUTS2 (EU)	2
Parish (UK)	2
Community association (Germany)	1
Environmentally Sensitive Area (Scotland)	1
NUTS4 (France)	1
Small Agricultural Region (France)	1
District (UK)	1
Region (UK)	1
Grant total	42

Table A5. Focus of papers.

Focus	Count
Low input farming	1
Best Management Practices for Water	1
Conservation measures	1
Conservation tillage	1
Environmental Sensitive Areas (agri-environmental scheme)	1
Environmentally focused area-based measures under the Bulgarian Rural Development Programme (RDP)	1
EU agri-environmental schemes	1
EU agri-environmental schemes (measure 214), organic farming, integrated farming, meadows and grazing payments	1
EU agri-environmental schemes (measure 214): bird conservation (total of 12 options); water habitats (total of 10 options); and habitat management (total of 32 options)	1
Fallow land	1
Fertiliser and pesticide reduction technologies into three categories: labour, capital, and skill-intensive technologies	1
Green control techniques (integrated pest management)	1
Natural Capital-related Rural development Funds	1
No tillage; conservation agriculture	1
Organic farming	24
Organic farming; integrated production	1

Table A6. List of variables that have a significant spillover effect as estimated through spatial Durbin and SLX models.

Variable	No authors (original)	No of authors (spatial)	Significant for X studies	Significant for X spatial models	Count +	Count -
Age of household head	9	5	4	4	1	3
% of progressive-environmental voters	3	1	1	3	3	0
Land values	2	1	1	3	2	1
Average commute time	1	1	1	3	0	3
Gender (male)	6	4	2	2	0	2
Risk attitude (Likert)	2	2	2	2	1	1
Number of workers	2	2	2	2	1	1
Livestock units per ha or per farm	5	2	2	2	0	2
Nature conservation (% of area, binary, or conservation receipts)	10	1	1	2	1	1
Total retail sales	1	1	1	2	1	1
Average farm income	1	1	1	2	0	2
Number of operations participating in crop insurance	1	1	1	2	0	2
Education of household head in years	11	6	3	1	1	0
Knows other organic farmers	2	2	2	1	1	0
Amenities (landscape, summer, winter)	3	2	2	1	0	1
On-farm processing	1	1	1	1	1	0
On-farm sales	1	1	1	1	1	0
Agri-tourism	2	1	1	1	1	0
Pasture farm	1	1	1	1	1	0
Mixed arable farm	1	1	1	1	1	0
Distance to road	2	1	1	1	1	0
Receipts from agricultural services	1	1	1	1	1	0
% of holders with formal agri or technical education	4	1	1	1	1	0
No of association and/or cooperative memberships	4	1	1	1	1	0
RDP payment for organic farming	2	1	1	1	1	0
Degree of cognition about control measures	1	1	1	1	1	0
Degree of cognition about the danger of chemicals	1	1	1	1	1	0
Frequency in communication with neighbours (Likert)	1	1	1	1	1	0
Strength of media publicity (Likert)	1	1	1	1	1	0
Neighbours appreciate if I apply new measures	1	1	1	1	1	0
Positive health effects associated with practices	1	1	1	1	1	0

No of topics that members of the neighbourhood network received extension on	1	1	1	1	1	0
Environmental attitude (Likert)	1	1	1	1	1	0
Drivers for adopting BMP: industry info	1	1	1	1	1	0
Drivers for adopting BMP: self-initiated,	1	1	1	1	1	0
Staff training	1	1	1	1	1	0
Perennial farm	1	1	1	1	0	1
Intensive livestock farm	1	1	1	1	0	1
Horticultural farm	1	1	1	1	0	1
UAA	5	1	1	1	0	1
Part time occupiers, % of or binary	4	1	1	1	0	1
Years of planting rice	2	1	1	1	0	1
Frequency of using magazines, tv, etc for information	2	1	1	1	0	1
Positive productivity affects neighbours plot	1	1	1	1	0	1
Profit orientation (Likert)	1	1	1	1	0	1
Barriers to adopting BMP: lack of info	1	1	1	1	0	1