AgBioForum, 21(2): 127-134. ©2018 AgBioForum.

Spatial Pattern of CAP Measures Promoting Agroforestry in Hungary

Arnold Csonka, Tibor Bareith, and Veronika Alexandra Gál
Kaposvár University Faculty of Economics, Hungary

Imre Fertő
Kaposvár University Faculty of Economics and Hungarian Academy of Sciences Institute of Economics, Centre for Economic and Regional Studies

Agroforestry is a sustainable form of land management that optimizes the use of natural resources. The current EU Common Agricultural Policy offers several measures to promote agroforestry activities. The aim of the paper is to evaluate the spatial pattern of agroforestry supports and identify the environmental factors driving demand for supports in Hungary, using highly disaggregated regional data. Cluster analysis suggests that rural land in Hungary can be effectively segmented into five groups according to agricultural and natural resource endowments. The five groups cover different farming systems including extensive land use, forestry systems, intensive small-scale farming, balanced land use, and conventional agriculture. The revealed cluster structure and characteristics may help develop strategies to improve the efficient implementation of agroforestry and agri-environmental measures. It implies that decision-makers should identify target areas where agroforestry adoption cannot be supported spontaneously by agglomeration effects and therefore it needs to be supported by education and innovation networks.

Key words: agroforestry, CAP, cluster analysis, nonparametric tests.

Introduction

Agroforestry is a land management practice which intentionally integrates woody vegetation with crop and/or animal systems to benefit from the resulting ecological and economic interactions (Burgess et al., 2015). The environmental services provided by agroforestry systems can be divided into four categories: (i) carbon sequestration, (ii) biodiversity improvements, (iii) enhanced soil productivity and conservation, (iv) water and air conservation (Jose, 2009). Agroforestry offers compelling synergies between adaptation (e.g., soil and water conservation, improved microclimate conditions, improved soil fertility) and mitigation (carbon sequestration) solutions to climate change (Lasco, Delfino, & Espaldon, 2014). Agroforestry systems can also improve livelihoods, enhance food security, and provide clean energy, contributing to sustainable rural development (Sharma et al., 2016). According to Kachova, Hinkov, Popov, Trichkov, and Mosquera-Losada (2016), agroforestry is a profitable, environmentally friendly, and sustainable technology for farmers living in less-developed rural areas. It is widely known that the development of rural areas has become a key point of Common Agricultural Policy (CAP) in the European Union (EU). Agroforestry systems are supported by the EU's rural development policies (RDPs) since they play a relevant role in producing positive social, economic, and environmental externalities (Gaspar, Escribano, & Mesias, 2016). Although agroforestry was poorly adopted in the CAP 2007-2013, recent evidence implies a better success in the CAP 2014-2020 (Santiago-Freijanes et al., 2018a). Mosquera-Losada et al. (2016) highlights five existing types of support for agroforestry on farms: (i) measures promoting silvoarable practices on farms, (ii) support for silvopasture farms, (iii) support for farms with high value trees, (iv) support for high nature value farms, and (v) forest farming activities. Despite the growing importance of agroforestry within the CAP, there is limited research evaluating these schemes, except recent papers by Santiago-Freijanes et al. (2018b), Moreno et al. (2018), Mosquera-Losada et al. (2018), and Pantera et al. (2018). Although some aspects of the spatial patterns of agroforestry schemes are already highlighted (den Herder et al., 2016; Santiago-Freijanes et al., 2018b), the drivers of agroforestry adoption is still not fully identified. The aim of this research is to explore the spatial patterning of the demand for agroforestry supports and identify its environmental and socio-economic drivers in Hungary. More specifically, we investigate (i) the spatial cluster structure of Hungarian municipalities based on potential for agroforestry, (ii) whether these clusters differ significantly in their tendency to run agroforestry or other agri-environmental projects. In contrast to previous papers, we focus on the demand for agroforestry support at a highly disaggregated regional level.

Theoretical Background

The distribution of new agricultural technologies is strongly differentiated in space (Berger, 2001; Minten & Barrett, 2007; Genius, Koundouri, Nauges, & Tzouvelekas, 2013). As mentioned in the introduction, the spread of agroforestry is strongly motivated by CAP subsidies. However, natural and ecological conditions provide additional incentives which can influence the implementation of agroforestry technologies in a given area. Reisner, de Filippi, Herzog, and Palma (2007) employed broad-resolution spatial data on soil, climate, topography, and land cover to identify potential agroforestry target regions in Europe. Their results show that silvoarable agroforestry has been implemented efficiently throughout the continent. Furthermore, due to their wide variety, agroforestry technologies can be adopted both in tropical and temperate areas of Earth (den Herder et al., 2016). To sum up, the spread of different agroforestry systems is not limited by natural conditions in Europe. Despite this fact, the spatial distribution of agroforestry is unequal across Europe. The highest frequency of agroforestry systems is in the southern countries while there is a very low density of agroforestry in other regions of Europe (den Herder et al., 2016). Since this spatial inequality cannot be explained by the variety of natural conditions, other factors should be explored to explain it.

Neupane, Sharma, and Thapa (2002) developed a complex framework for exploring agroforestry adoption at the household level. The factors of agroforestry adoption can be divided into four main categories:

- community characteristics (access to market, infrastructure, technology, education, local knowledge, extension and employment opportunities, natural environment);
- household characteristics (socioeconomic factors, resources, extension contracts, membership in farmers' groups, needs);
- activity of local NGOs and farmers' groups (coordination, local level participation, awareness campaigns, meetings, local resource mobilization, moral support);
- activity of external agroforestry organization (design and dissemination of appropriate agroforestry technology, design of farmers' visits, demonstration farms and on-farm trials, provision of material support, training, technical know-how, and extension).

These factors influence the awareness of agroforestry, then the attitude towards agroforestry, and finally the adoption of agroforestry. Note that the natural environment forms only a small part of the model, while the majority of factors are related to social and/or economic dimensions.

Zerihun, Muchie, and Worku (2014) provide a similar complex framework for analyzing factors in the adoption of natural resources management, especially in the adoption of agroforestry systems. They point out that the sustainable adoption of agroforestry is affected by

- contemporary global changes and macro policies;
- institutional factors, e.g., operational rules, collective choice rules, and constitutional rules;
- physical and technical attributes of resources;
- external agents (users, resource users, and stakeholders);
- other factors like risk, household preferences, resource endowments, incentives (e.g., subsidies, prices, and expectations), and biophysical factors.

Cooper and Denning (2000) argue that the scaling up of agroforestry innovations is influenced by ten different factors, including learning-by-doing practices, technology options, knowledge sharing and extension approaches, institutional capacity, policy and market options, strategic partnerships, and available germplasms.

Louah, Visser, Blaimont, and de Cannière (2017) highlight the importance of path dependency and cognitive lock-in as barriers to the development of temperate agroforestry. Usually, farmers accept common old technologies as established and unquestionable, so they react negatively to new technologies. Path dependency and cognitive lock-in effects can be reduced by ecological education and learning within innovation networks. Based on a semi-quantitative questionnaire, Sereke et al. (2016) concluded that payments for ecosystem services (e.g., agroforestry systems) cannot change attitude lock-in as long as farmers' expectations and knowledge are not appropriately addressed. It therefore appears that agroforestry-related CAP subsidies should be supported by well-designed training systems and innovation networks in order to motivate agroforestry adoption.

Beyond these drivers, there is another factor which may have a positive effect on the diffusion of innovative agricultural technologies, the agglomeration effect or agglomeration externality. Agglomeration effects are those external economic effects from which a firm can

Table 1. The main driving factors of agroforestry adoption.

Factor categories	Source
Natural resources and ecological factors	Reisner et al. (2007), den Herder et al. (2016)
Agricultural demography and resources	Neupane et al. (2002), Kant and Lehrer (2004), Zerihun et al. (2014)
Markets, institutions and policies	Cooper and Denning (2000), Neupane et al. (2002), Kant and Lehrer (2004), Zerihun et al. (2014)
Networks and partnerships	Cooper and Denning (2000), Neupane et al. (2002), Louah et al. (2017)
Expectations and technological knowledge	Sereke et al. (2016)
Path dependency and cognitive lock-in	Louah et al. (2017)
Agglomeration effects	Nyblom et al. (2003), Schmidtner et al. (2012), Allaire et al. (2015)

Source: own compilation

benefit by being located at the same place as one or more other firms (Malmberg et al, 2000). The spatial proximity leads to cost reduction (e.g., production costs may be lowered by the possibility of sharing resources, or transaction costs may be reduced by the enhanced interaction between supplier and customers). In addition, spatial proximity may increase the level of knowledge sharing between the firms.

Recent studies highlight the relevance of agglomeration effects in agriculture (Allaire et al., 2015; Nyblom, Borgatti, Roslakka, & Salo, 2003; Schmidtner et al., 2012). An additional strand of research analyzes spatial differences in the diffusion of alternative agriculture technologies (e.g., organic farming), based on concentration indices, at different levels and for different countries (Frederiksen & Langer, 2004; Ilbery, Holloway, & Arber, 1999; Ilbery & Maye, 2011; Risgaard, Frederiksen, & Kaltoft, 2007). In short, the agglomeration effect is identified as an important driver shaping the spatial diffusion of agricultural technologies. Based on this short review, the driving factors of agroforestry adoption are summarized in Table 1.

Figure 1 shows the conceptual framework of our analysis. We focus only on agricultural demography and resources; the other six factors will be the subject of further research. The model suggests that the agroforestry adoption potential of a spatial unit depends on the presence of small-scale farms, intensive (conventional) agricultural land use, extensive agricultural land use, and forestry. Therefore, spatial units can be classified based on these factors. It is assumed in our framework that differences in agroforestry potential lead to differences in the tendency to adopt agroforestry systems among land use types.

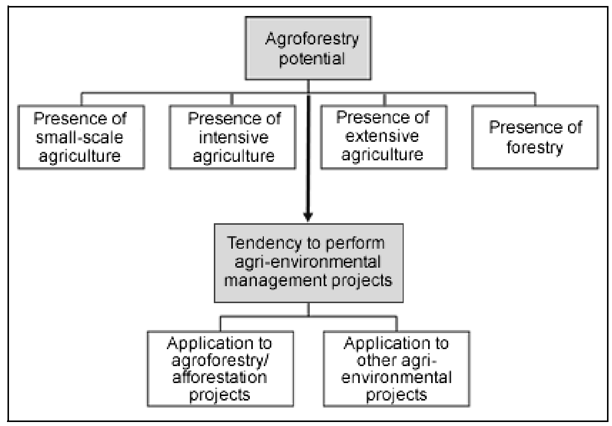

Figure 1. Conceptual framework of the preliminary research.
Source: Own compilation

Material and Methods

Empirical Methodology

We used a three-stage approach to investigate the spatial patterns of Hungarian municipalities (local administrative units), based on agroforestry potential factors, and test whether there are significant differences in the tendency to adopt agroforestry among the spatial clusters.

In the first stage, we employ a two-step cluster analysis procedure to identify clusters within the dataset of 3155 Hungarian municipalities, based on four continuous agroforestry potential variables. Virtually, our spatial sample completely covers the whole area of Hungary at the municipality level. The similarity between clusters is computed by a log-likelihood measure. The number of clusters is determined by Schwarz's Bayesian Information Criterion (BIC). Before running the cluster analysis, each variable was standardized to the same scale (with a mean of 0 and a standard deviation of 1) using z-score transformation. Four variables

Table 2. Description of variables.

Role	Variable code	Variable name (year)	Proxy for factor	Dimension
Clustering variables	R_SMALL	Ratio of registered primary agricultural producer's income (2012)	Presence of small-scale agriculture	(HUF/HUF)
	R_INTAG	Ratio of arable lands and orchards (2012)	Presence of intensive agriculture	(ha/ha)
	R_EXTAG	Ratio of meadows, pasture lands and natural grasslands (2012)	Presence of extensive agriculture	(ha/ha)
	R_FOR	Ratio of Forests (2012)	Presence of forestry	(ha/ha)
Validation variables	P_AGFOR	Amount of aid applications to run agroforestry projects (2009-2015)	Tendency to perform agroforestry projects	HUF/ha
	P_OTHER	Amount of aid applications to run other agri-environmental projects (2009-2015)	Tendency to perform other agri-environmental projects	HUF/ha

Source: own compilation

were involved in cluster analysis: R_SMALL, R_INTAG, R_EXTAG, R_FOR (details are in Table 2).

In the second stage, the revealed cluster structure is validated by two different nonparametric tests including Kruskal-Wallis H test and Median test. The Kruskal-Wallis H test, an extension of the Mann-Whitney U test, is the nonparametric analog of one-way analysis of variance and detects differences in distribution location. The median test, which is a more general test (but not as powerful), detects distributional differences in location and shape. The Kruskal-Wallis H test and the median test assume that there is no a priori ordering of the k populations from which the samples are drawn. The validation is based on two factors: amount of aid applications for agroforestry projects (P_AGFOR) and amount of aid applications for other agri-environmental projects (P_OTHER).

The final stage dealt with mapping and visualization of clusters revealed and validated in first two stages. Using QGIS geographical information software, a cluster map was created where the spatial units were marked by different colors representing cluster membership. This approach reveals the geographical shape and context of clusters.

Variables and Data

The empirical analysis is based on data provided by TEIR (Hungarian Information System of Regional Development and Spatial Planning). The description of variables is in Table 2.

The upper part of the table describes the clustering variables. Although the period of validation data begins in 2009, the oldest clustering data overlapping each variable is only available from 2012. R_SMALL is originally provided by National Tax and Customs Administration to the TEIR system and represents the share of small-scale farm income to the whole income of a given municipality. The next three variables are calculated from the land use data of the CORINE 2012 database and show the ratio of agricultural and forested area to the whole administrative area of a given municipality.

Validation variables are in the bottom portion of the table. The tendency to perform agroforestry or other agri-environmental projects is estimated by the amount of aid applications to support these projects per hectare. We use proxies aggregated across the whole investigation period.

Results and Discussion

Agroforestry Potential Clusters in Hungary

The two-step cluster analysis based on BIC identified five clusters. Table 3 shows the characteristics of the clusters including both clustering and validation variables. The number of municipalities in each cluster and the significance of the one-way ANOVA analysis confirming the existence of significant differences in the means of each variable for the five-cluster solution can be observed in Table 3.

As the F-statistic indicates a significant difference, individual differences were explored using the all pairwise post hoc test (Tukey's test) for multiple comparisons (see Table 4).

The analysis of Table 4 suggests that the two variables related to agricultural land use (R_INTAG and R_EXTAG) are powerful in differentiating each cluster. R_SMALL is particularly useful to differentiate cluster three from all other clusters. R_FOR is especially suitable to differentiate clusters two and five. In order to support the cluster characterization process, the results

Table 3. Main characteristics of agroforestry potential clusters.

Two-step method	R_SMALL mean	R_INTAG mean	R_EXTAG mean	R_FOR mean	P_OTHER mean	P_AGFOR mean
	Cluster					
Cluster 1 *n = 599*	0.0011	0.2097	0.6585	0.0839	6,882.8511	482.3115
Cluster 2 *n = 513*	0.0021	0.3175	0.2921	0.2816	11,581.7030	1,067.5490
Cluster 3 *n = 145*	0.0390	0.6651	0.1993	0.0944	5,547.4607	598.6258
Cluster 4 *n = 889*	0.0015	0.4951	0.2775	0.0807	4,068.8652	832.8106
Cluster 5 *n = 1,009*	0.0030	0.7705	0.0798	0.0717	3,100.0795	494.4591
Total *n = 3,155*	0.0037	0.5079	0.2854	0.1117	5,582.8287	685.4630
F-ratio	962.110	1,839.628	1,944.752	1,032.640	17.352	3.131
Significance level	0.000	0.000	0.000	0.000	0.000	0.014

Source: own calculations

Table 4. Significance of differences in mean factor.

Variables	1-2	1-3	1-4	1-5	2-3	2-4	2-5	3-4	3-5	4-5
	Clusters compared									
R_SMALL	NS	***	NS	***	***	NS	NS	***	***	***
R_INTAG	***	***	***	***	***	**	***	***	***	***
R_EXTAG	***	***	***	***	***	NS	***	***	***	***
R_FOR	***	NS	NS	**	***	***	***	NS	***	*
P_AGFOR	*	NS	NS	NS	NS	NS	*	NS	NS	NS
P_OTHER	***	NS	NS	**	*	***	***	NS	NS	NS

Source: own calculations
****, **, *: significance level is either 1, 5 or 10%, respectively. NS=not significant*

of ANOVA and post hoc tests for validation variables (P_AGFOR and P_OTHER) are also shown in Tables 3 and 4. However, considering the non-normal distribution of these variables, the final validation of the cluster structure will be discussed based on non-parametric tests in the next subsection.

Based on the relative differences in clustering variables, the clusters have quite diverse characteristics. This diversity was used to assign names to the clusters.

Cluster 1 (extensive land use group) represents municipalities with a low proportion of small-scale farming and forested areas, where the amount of extensive agricultural areas exceeds the volume of intensive agricultural land use. The tendency to run agroforestry projects is the lowest in this group while activity in the field of other agri-environmental projects is quite high.

Cluster 2 (forestry systems group) is clearly dominated by forested areas, whereas the presence of small-scale farming and intensive agriculture is relatively low. The tendency to run agroforestry and other agri-environmental projects is by far the highest in this group.

Both small-scale farming and intensive agricultural land are dominant in Cluster 3 (small-scale farming group). The presence of small-scale farms might create an ideal environment for agroforestry adoption. However, the moderately low rate of extensive agriculture limits the tendency to establish agri-environmental and agroforestry projects.

Cluster 4 (balanced land use group) is theoretically not suitable for agroforestry adoption. The presence of agricultural land use (both extensive and intensive) is slightly below average, while the small-scale farming ratio and the proportion of forested areas is relatively low. Despite this, the demand for agroforestry projects is high (the second highest) in this group.

Cluster 5 (conventional agriculture group) is characterized by the dominance of intensive agriculture. The proportion of extensive agricultural lands and forests are by far the lowest of all clusters. The demand for agroforestry and agri-environmental subsidies is also very low.

Our results suggest that the presence of intensive agricultural land use hinders agroforestry adoption, as assumed by the theories of cognitive lock-in and path dependency (Louah et al., 2017; Sereke et al., 2016). Estimations also imply that municipalities with a high ratio of small-scale farming have a lower tendency to

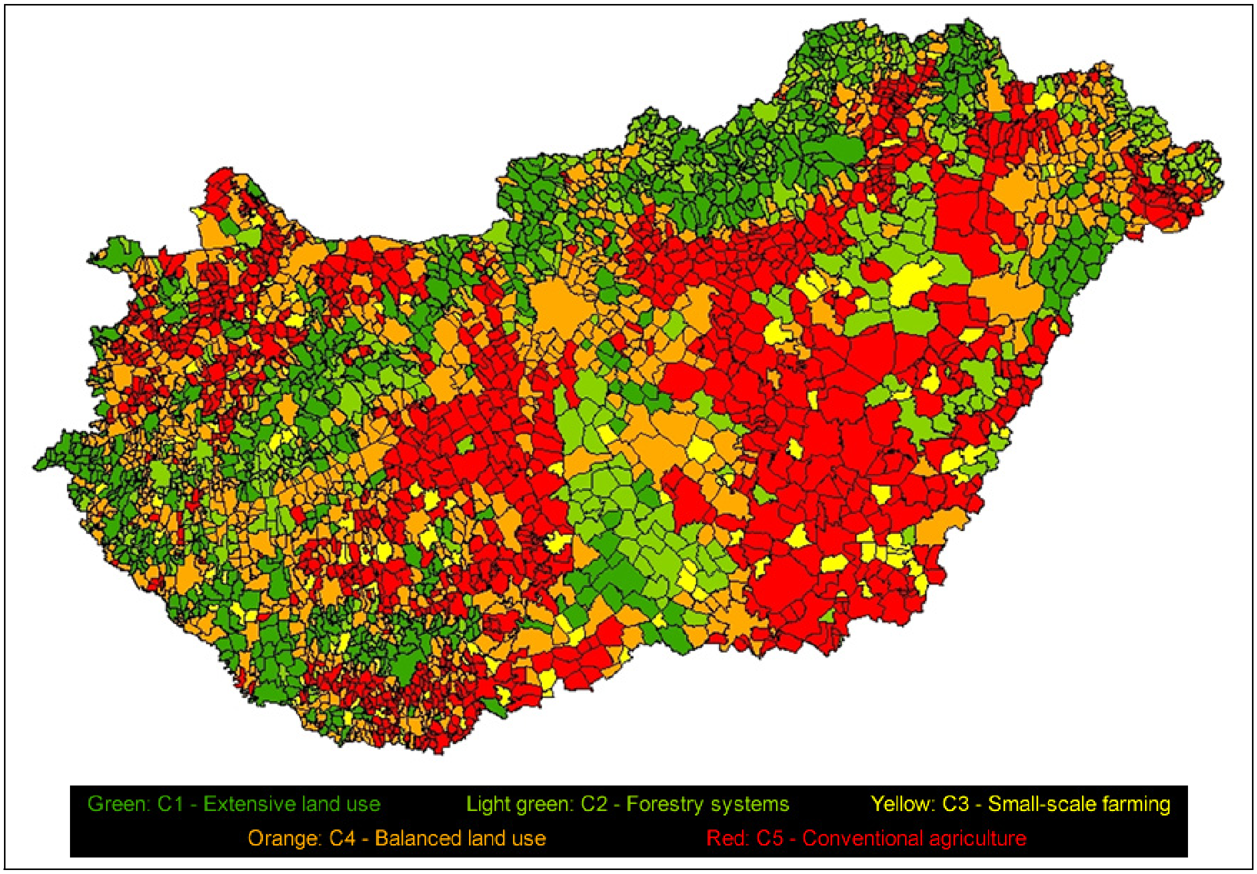

Figure 2. Cluster map of Hungarian agroforestry potential at LAU-2 level.
Source: Own constructions

adopt agroforestry, contrary to Neupane et al. (2002), Kant and Lehrer (2004), and Zerihun et al. (2014). The impact of cognitive lock-in and path dependency appears to be higher in these municipalities.

Validation of the Cluster Structure

The differences in validation variables among the clusters were tested by nonparametric tests to decide whether the different combinations of clustering attributes significantly affect the tendency to adopt agroforestry and agri-environmental technologies. Table 5 shows the results of the nonparametric tests.

Both the Kruskall-Wallis H test and the Median test demonstrate that the cluster structure is valid. Differences in agroforestry potential characteristics lead to significant differences in the tendency to run agroforestry or other agri-environmental projects. The validation supports the impact of agroforestry potential factors according to the literature seen in Table 1.

Table 5. Nonparametric test statistics for validation variables.

	Kruskal-Wallis H test		Median test	
	P_AGFOR	P_OTHER	P_AGFOR	P_OTHER
Chi-Square	12.113	172.024	11.365	112.682
df	4	4	4	4
Asymp. Sig.	0.017	0.000	0.023	0.000

Source: own calculations

Cluster Map of Hungarian Agroforestry Potential

Figure 2 shows the geographic distribution and shapes of the clusters. There are three quite agglomerated clusters: C1 (Extensive land use), C2 (Forestry systems) and C5 (Conventional agriculture). C1 and C5 together represent the very lowest level of tendency to adopt agroforestry. On the contrary, C2 embodies the highest demand for agri-environmental and agroforestry supports. The spatial distribution of the less extreme clusters, C3 and C4, is more fragmented. These results confirm the relevance of agglomeration and spillover effects (Allaire et al., 2015; Nyblom et al., 2003; Schmidtner et al., 2012) in the diffusion of new agricultural technologies.

The geographic fragmentation of C3 and C4 mean that the adoption of new technologies cannot be supported by spontaneous agglomeration effects. Therefore, the role of ecological education and innovation networks (Louah et al., 2017; Sereka et al., 2016) is very important in these groups. With the help of training and innovation networks, the spread of agroforestry among the neighboring areas could become faster and more homogenous.

Conclusions

The aim of this research is to investigate the spatial pattern of demand for agroforestry supports and identify the environmental factors driving adoption in Hungary, using municipality level data. Our results provide additional knowledge about the spatial differences of demand for agroforestry subsidies in areas of Hungary with unused agroforestry potential. In addition, our models highlight the potential barriers to successful adoption of agroforestry and agri-environmental measures. We recommend identifying target areas where agroforestry adoption cannot be supported spontaneously by agglomeration effects and therefore need to be supported by education and innovation networks. Our three-stage approach can be extended by taking into account other potential socio-economic drivers of adoption of agroforestry schemes.

Our results confirm that the factors influencing agroforestry adoption can be extended from farm level to a regional level. The theoretical considerations of agroforestry adoption are also valid at the regional level. In line with recent studies, agroforestry systems are viable technologies mainly for small-scale farmers. Our findings show that small-scale farming is strongly linked to conventional and intensive agricultural land use in Hungary. Risk-averse small-scale farmers tend to be hesitant to replace well-known conventional technologies with a new, more extensive technology like agroforestry.

The main limitation of this study is our ability to measure precisely the degree of spatial clustering and agglomeration effects using descriptive visual depiction of the identified clusters and their geographic agglomeration. Therefore, we see a need for further research exploring the reasons behind the observed agglomeration effects by applying a spatial econometric approach.

References

Allaire, G., Poméon, T., Maigné, E., Cahuzac, E., Simioni, M., & Desjeux, Y. (2015). Territorial analysis of the diffusion of organic farming in France: Between heterogeneity and spatial dependence. *Ecological Indicators*, *59*, 70-81.

Berger, T. (2001). Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, *25*(2-3), 245-260.

Burgess, P.J., Crous-Duran, J., den Herder, M., Dupraz, C., Fagerholm, N., Freese, D., et al. (2015, February 27). *AGFORWARD project periodic report: January to December 2014*. Bedfordshire, UK: Cranfield University.

Cooper, P.J.M., & Denning, G.L. (2000). *Scaling up the impact of agroforestry research* (Report of the agroforestry dissemination workshop). Nairobi, Kenya.

den Herder, M., Moreno, G., Mosquera-Losada, M.R., Palma, J.H.N., Sidiropoulou, A., Santiago-Freijanes, J., et al. (2016, August). *Current extent and stratification of agroforestry in the EU27* (Deliverable 1.2 for AGFORWARD 613520). Auch, France: AGFORWARD. Available on the World Wide Web: http://agforward.eu/index.php/en/current-extent-and-trends-of-agroforestry-in-the-eu27.html.

Frederiksen, P. and Langer, V. (2004). Localisation and concentration of organic farming in the 1990—The Danish case. *Tijdschrift voor Economische en Sociale Geografie*, *95*(5), 539-549.

Gaspar, P., Escribano, M., & Mesias, F.J. (2016). A qualitative approach to study social perceptions and public policies in dehesa agroforestry systems. *Land Use Policy*, *58*, 427-436.

Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2013). Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics*, *96*(1), 328-344.

Ilbery, B., Holloway, L., & Arber, R. (1999). The geography of organic farming in England and Wales in the 1990s. *Tijdschrift voor Economische en Sociale Geografie*, *90*(3), 285-295.

Ilbery, B., & Maye, D. (2011). Clustering and the spatial distribution of organic farming in England and Wales. *Area*, *43*(1), 31-41.

Jose, S. (2009). Agroforestry for ecosystem services and environmental benefits: An overview. *Agroforestry Systems*, *76*(1), 1-10.

Kachova, V., Hinkov, G., Popov, E., Trichkov, L. and Mosquera-Losada, R. (2016). Agroforestry in Bulgaria: history, presence status and prospects. Agroforestry Systems 92(3): 655-665.

Kant, S., & Lehrer, E. (2004). A framework for institutional analysis of agroforestry systems. In J.R.R. Alavalapati & D.E.

Mercer (Eds.), *Valuing agroforestry systems: Methods and applications* (pp. 279-302). Dordrecht: Kluwer Academic.

Lasco, R.D., Delfino, R.J.P., & Espaldon, M.L.O. (2014). Agroforestry systems: Helping smallholders adapt to climate risks while mitigating climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(6), 825-833.

Louah, L., Visser, M., Blaimont, A., & de Cannière, Ch. (2017). Barriers to the development of temperate agroforestry as an example of agroecological innovation: Mainly a matter of cognitive lock-in? *Land Use Policy*, *67*, 86-97.

Minten, B., & Barrett, C.B. (2007). *Agricultural technology, productivity, poverty and food security in Madagascar* (Strategies and Analyses for Growth and Access [SAGA] Working Paper). US Agency for International Development.

Moreno, G., Aviron, S., Berg, S., Crous-Duran, J., Franca, A., García de Jalón, S., et al. (2018). Agroforestry systems of high nature and cultural value in Europe: Provision of commercial goods and other ecosystem services. *Agroforestry Systems*, *92*, 877-891.

Mosquera-Losada, M.R., Santiago-Freijanes, J.J., Pisanelli, A., Rois, M., Smith, J., den Herder, M., et al. (2018). Agroforestry in the European common agricultural policy. *Agroforestry Systems*, *92*, 1117-1127.

Mosquera-Losada, M.R., Santiago-Freijanes, J.J., Pisanelli, A., Rois-Diaz, M., Smith, J., den Herder, M., et al. (2016). *Extent and success of current policy measures to promote agroforestry across Europe* (Deliverable 8.23 for EU FP7 Research Project AGFORWARD 613520). Bedfordshire, UK: Cranfield University.

Neupane, R.P., Sharma, K.R., & Thapa, G.B. (2002). Adoption of agroforestry in the hills of Nepal: A logistic regression analysis. *Agricultural Systems*, *72*(1), 177-196.

Nyblom, J., Borgatti, S., Roslakka, J., & Salo, M.A. (2003). Statistical analysis of network data—An application to diffusion of innovation. *Social Networks*, *25*(2), 175-195.

Pantera, A., Burgess, P.J., Mosquera-Losada, R., Moreno, G., López-Díaz, M.L., Corroyer, N., et al. (2018). Agroforestry for high value tree systems in Europe. *Agroforestry Systems*, *92*, 945-959.

Reisner, Y., de Filippi, R., Herzog, F., & Palma, J. (2007). Target regions for silvoarable agroforestry in Europe. *Ecological Engineering*, *29*(4), 401-418.

Risgaard, M.L., Frederiksen, P., & Kaltoft, P. (2007). Socio-cultural process behind thedifferential distribution of organic farming in Denmark. *Agriculture and Human Values*, *24*(4), 445-459.

Santiago-Freijanes, J.J, Pisanelli, A., Rois-Díaz, M., Aldrey-Vázquez, J.A., Rigueiro-Rodríguez, A., Pantera, A., et al. (2018a). Agroforestry development in Europe: Policy issues. *Land Use Policy*, *76*, 144-156.

Santiago-Freijanes, J.J, Rigueiro-Rodríguez, A., Aldrey, J.A., Moreno, G., den Herder, M., Burgess, P., & Mosquera-Losada, M.R. (2018b). Understanding agroforestry practices In Europe through landscape features policy promotion. *Agroforestry Systems*, *92*, 1105-1115.

Schmidtner, E., Lippert, C., Engler, B., Häring, A.M., Aurbacher, J., & Dabbert, S. (2012). Spatial distribution of organic farming in Germany: Does neighbourhood matter? *European Review of Agricultural Economics*, *39*(4), 661-683.

Sereke, F., Dobricki, M., Wilkes, J., Kaeser, A., Graves, A.R., Szerencsits, E., & Herzog, F. (2016). Swiss farmers don't adopt agroforestry because they fear for their reputation. *Agroforestry Systems*, *90*(3), 385-394.

Sharma, N., Bohra, B., Pragya, N., Cianella, R., Dobie, P., & Lehmann, S. (2016). Bioenergy from agroforestry can lead to improved food security, climate change, soil quality, and rural development. *Food and Energy Security*, *5*(3), 165-183.

Zerihun, M.F., Muchie, M., & Worku, Z. (2014). Determinants of agroforestry technology adoption in Eastern Cape Province, South Africa. *Development Studies Research*, *1*(1), 382-394.

Acknowledgement

The research was supported by EFOP-3.6.2-16-2017-00018 in Kaposvár University project.