The Effect Of Spatial Market Structure On The Acreage Of Biodiversity-Improving Protein Crops: Evidence From Germany

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Abstract:

One of the challenges currently facing Europe's agri-food system is the availability of sustainable, high-quality protein for animal feed in regions of intensive animal production. The production of grain legumes holds the potential to significantly increase the availability of protein feed in Europe, thereby raising the biodiversity contribution of cropland. Germany is a major protein importer (especially in terms of soy), while grain legumes' acreage remains limited and volatile. Despite agronomic considerations, one reason for this might be the noncompetitive structure of grain legume traders. Using district data from 400 German regions, a spatial stochastic frontier analysis is applied to estimate the effect of the spatial market structure on the diffusion of grain legume growing. The analysis shows that the number of agricultural traders in close spatial proximity is significantly and positively associated with farmers' decision to grow grain legumes. Improving the marketing structure e.g. by establishing marketing cooperatives or investigating potential market power among traders could be promising strategies to capture some of the currently under-utilized protein crop potential in Germany.

Keywords: Spatial Stochastic Frontier, Spatial Weights, Grain Legumes, Market Access, Adoption

JEL: Q02, Q11, Q13

1. Introduction

Grain legumes, encompassing a diverse array of crops such as field beans, peas, lupins and soybeans, occupy a significant position in global agriculture, serving as essential protein sources for food and feed use (Kumar et al., 2022; Voisin et al., 2014). Their contribution to developing resilient and sustainable land use systems, both conventional and organic, is immense: Cultivation of grain legumes reduces disease and weed pressure, and thus also the need for chemical pesticides (Böhm et al., 2020). Legumes also improve soil quality by loosening the soil structure, fixing atmospheric nitrogen, providing nitrogen for the subsequent crop, and increasing the biodiversity of the production system (Ditzler et al., 2021; Fugeray-Scarbel & Lemarié, 2024; Reckling et al., 2020; Zander et al., 2016). The recognition of the positive effects of grain legume cultivation is reflected in the expansion of cultivation areas and production volumes in the EU-27. After stagnating for almost two decades, the area devoted to grain legumes, particularly soybeans, has more than doubled in the last decade (Bues et al., 2013; Eurostat, 2023). Nevertheless, grain legumes still account for only 6 % of the total arable land in the EU (Eurostat, 2023).

In 2022, France, Poland, Spain, Germany and Lithuania were the main grain legume producing countries in the EU (Eurostat, 2023). However, some of these countries experienced a relatively low protein self-sufficiency, as in particular, Germany, Spain and Italy were also the largest importers of soybeans in the EU (FAOstat, 2024). This reflects their substantial protein demand driven by large livestock and feed industries, which domestic grain legume production alone cannot fully satisfy.

As the largest importer of protein crops in the EU (FAOstat, 2024), Germany stands out as an important market for grain legumes due to its large and intensive livestock and dairy sectors. These sectors demand vast amounts of high-quality plant protein for compound feed, underscoring the ongoing reliance on imports despite regional production capacity (BMEL, 2020). Soisontes et al. (2023) and Zerhusen-Blecher et al. (2016) point out that the compound feed industry and its demand for non-GMO has a strong impact on the area under grain legumes in Germany and thus on the country's protein self-sufficiency. Given the favourable soil conditions for grain legumes in many parts of Germany (Roßberg & Recknagel, 2017), expanding their production could contribute to reducing the country's substantial protein imports. However, only 2.5 % (in 2022) of Germany's arable land was cultivated with grain legumes (Statistisches Bundesamt, 2023), well below the EU average of 6 %. A key economic explanation lies in the principle of comparative advantage: German farmers often face lower profitability with grain legumes than with other crops, such as cereals or oilseeds.

As noted by Soisontes et al. (2023) and Mittag and Hess (2025) grain legumes in Germany tend to have relatively low producer prices, while price formation in this market is characterized by limited transparency due to fragmented trade structures and incomplete price reporting. This weakens the competitiveness of grain legumes from the producer's perspective and hence their bargaining power.

Moreover, as discussed later in this paper, gross margins from cereals or canola in Germany can exceed those of grain legumes by a factor of up to three, making legumes a less attractive economic choice under current conditions. Thus, the relatively low acreage of grain legumes is largely a reflection of Germany’s comparative disadvantage in their production both relative to other crops domestically and relative to legume-producing regions elsewhere in the world. Nonetheless, market conditions may still influence these choices at the margin. Based on a delphi-study by Soisontes et al. (2023), in addition to profitability, a lack of marketing structures could be the main reason for the lack of competitiveness and, hence, for the low acreage of grain legumes in Germany. However, the spatial market structure for local and regional trade in grain legumes in Germany and its potential influence on cultivation decisions and the resulting land use changes have so far not been analysed empirically.

A detailed understanding of the interactions between land use change and market access is crucial for developing efficient policies promoting sustainable land use. However, empirical studies of cropping decisions and, hence, land use have become rarer in recent years, especially outside developing countries, and are not generally used to inform land system policy-making.

Therefore, this paper examines the link between market access and land use change, specifically regarding the adoption of new crops in the German grain legume market. Market access is expected to play a pivotal role in shaping the spatial distribution and intensity of grain legume cultivation in Germany. To test this hypothesis, a spatial stochastic frontier analysis is applied.

By examining the interplay between market access and adoption decisions at a spatial scale on the producers' site, this paper aims to explain the market mechanisms that drive grain legume expansion in the German context and identify pathways for enhancing agricultural sustainability and resilience. In doing so, the study is positioned within applied economic questions at the intersection of bio-based agricultural production, market infrastructure, land-use dynamics, and sustainable rural development. It contributes to this discourse by providing empirical evidence and theoretical insights into the role of market infrastructure in shaping patterns of grain legume cultivation. While this study focuses on Germany, the results underscore the importance of understanding how market structure influences land-use decisions for cash crops more generally.

2. Status Quo and Theoretical Framework

2.1. Legume cultivation and trade in Germany

Assuming profit-maximising farmers, the cultivation of grain legumes occurs in locations that (a) are considered favourable for these crops due to their high cultivation suitability and (b) have sufficient market access through suitable infrastructure, low transportation cost and access to traders and elevators (silos) nearby. Therefore, the comparatively low acreage of grain legume crops in Germany could be related either to local- and farm specific opportunity cost, or to the regional structure of market access, or to both.

a) Farm-specific factors:

Not every grain legume crop can be grown in every location. Several factors, such as the various grain legumes' different climatic and location requirements, limit the geographical cultivation range. Roßberg and Recknagel (2017) identify regions in Germany suitable for grain legume cultivation, and Stephenson (2022) provides an updated assessment of this spatial distribution based on more recent climate data. However, their cultivation suitability maps indicate that grain legumes can be cultivated across large parts of Germany.

Barbieri et al. (2023) state that grain legumes significantly contribute to production efficiency, especially in organic production systems. As nitrogen availability can be limiting, especially in the absence of livestock, integrating grain legumes with symbiotic fixation of atmospheric nitrogen is essential for higher yields and improved quality of subsequent crops, e.g. grains, supply of ecosystem services and the adaptation of production systems to climate change (Bedoussac et al., 2014; Reckling et al., 2020). Thus, organic farms are more likely to introduce grain legumes in their crop rotation than conventional ones.

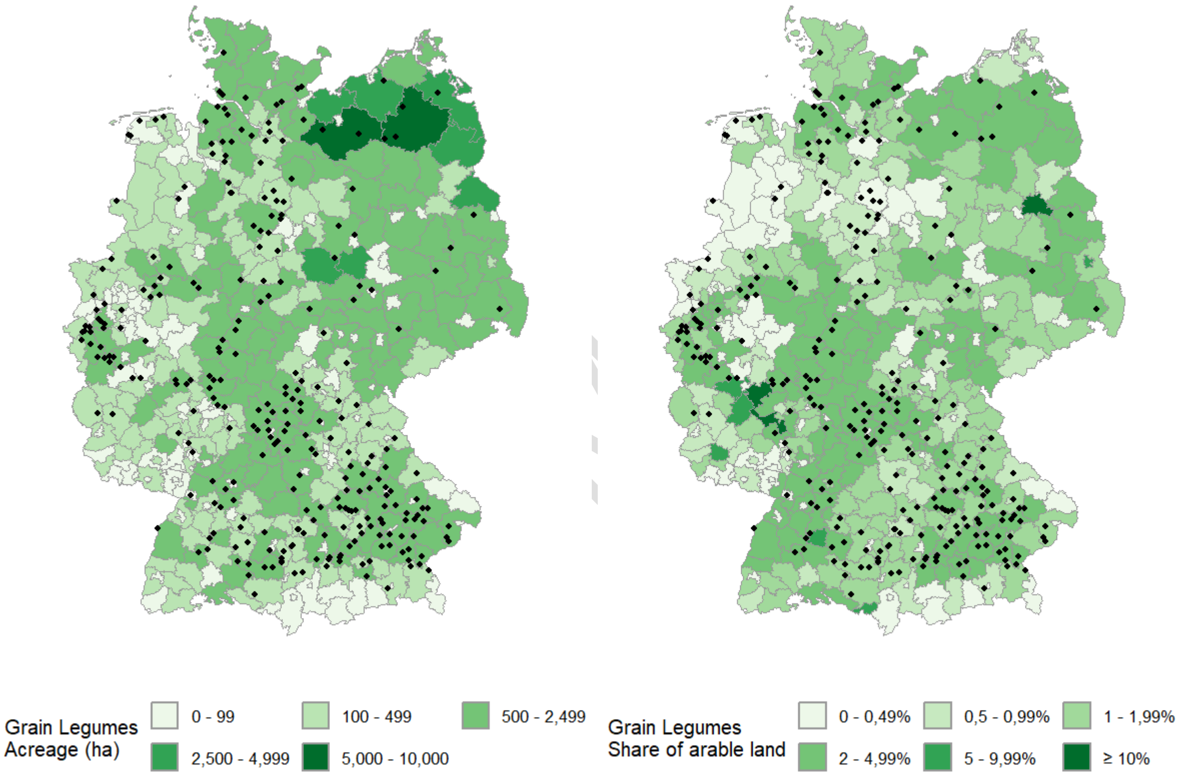
Regarding both conventional and organic crop rotations, Sponagel et al. (2021) state that cultivation decisions are often made in favour of the economically most profitable crops and negatively influence the decision to cultivate grain legumes.

However, despite potential economic disadvantages, several private and public initiatives try to encourage farmers to increase the share of grain legumes in their crop rotation. Namely, Legunet (Legunet, 2024) actively promotes both agronomic and ecological advantages of grain legume production in Germany. Legunet is a public initiative in Germany which offers nationwide projects, extension and advisory services to overcome potential knowledge gaps and information barriers. Despite private initiatives, farmers can also apply for subsidies supporting grain legume production. The geographical differentiation of political support schemes and measures that aim at providing incentives for cultivating grain legumes in Germany has been analysed by Bues et al. (2013) and Sponagel et al. (2021). Their analyses shows that support for grain legume cultivation is not uniform nationwide but adapted to regional conditions, which influences cultivation patterns.

b) Market structure for grain legume producers in Germany

The market structure of the legume trade in Germany can generally be described as non-transparent both regarding market access and price formation (Kezeya Sepngang et al., 2019). Zimmer and Böttcher (2021) have identified the lack of marketing structures, especially in northern Germany, as a significant reason for the low competitiveness in grain legume cultivation in Germany. According to Jouan et al. (2019), a pre-contract for grain legume crops is less common than for other crops from conventional arable farms, such as cereals or canola. Therefore, it can be assumed that selling cultivated grain legumes to regional agricultural traders is the most common practice.

Figure 1: Spatial distribution of agricultural traders interested in buying grain legumes and grain legume acreage per district (ha) (left) and share of grain legumes acreage per district (%) (right)



Source: Own representation based on data from the Union zur Förderung von Oel-und Proteinpflanzen e.V. (2025); traders indicated by small dots.

Figure 1 displays the location of all traders who commit to trading grain legumes in Germany (traders indicated by small dots).

Under climatic conditions in Germany, grain legumes often have to be harvested even though grain moisture is still higher than optimal, which limits transportability and storage stability (Roth, 2022). Magrini et al. (2016) report on the challenges of grain legume trade in France.

France has a more diversified product portfolio in grain legume trade than Germany. However, even in France the storage capacities for grain legumes are subject to very long payback periods due to the relatively low trade volumes. As a result, grain legumes are often neglected in storage investment strategies; actual lot sizes of grain legumes tend to get sold quickly in order to make room for crops of larger lot sizes that will fill silos completely and thus reduce average storage costs (Reindl et al., 2017).

Similar information on the German market for grain legumes was gathered through in-depth interviews with traders: According to the qualitative evidence from these interviews, small quantities of grain legumes block a typical trader's storage capacities, which are often designed for larger quantities, and from the perspective of a typical trading company this will render trading grain legumes on average less profitable compared to other crops (Mittag & Hess, 2025).

Specht (2009), Kezeya Sepngang, Stute, et al. (2018) and Soisontes et al. (2023) have explored sales structures of grain legumes in Germany based on qualitative interviews and stakeholder discussions. The authors cite a lack of interest among agricultural trading companies in grain legumes because large and homogeneous lots of any pre-defined quality would be scarce in supply, if not missing.

Moreover, on the supply side and due to comparatively low producer prices for grain legumes, farmers prefer to grow cereals and oilseed crops, which often offer a gross margin up to three times higher (Sponagel et al., 2021).

Thus, overall the price formation process for grain legumes in Germany can be described as typically fragmented, such that small lots of marketed quantities make domestic grain legumes even less profitable in comparison to other crops than would be the case under price formation that is not affected by the tendency of traders to empty silos quickly (Reckling et al., 2020). However, based on a Delphi study with stakeholders along the grain legume value chain, Soisontes et al. (2023) highlight that a reasonable price for home-grown and non-GMO protein feed ingredients would have excellent potential to increase the grain legume acreage in Germany. In summary, it seems that high transaction costs, which arise from farmers' search for information on sales structures and high transport costs, substantially reduce the economic attractiveness and cost-effectiveness of grain legume cultivation compared with competing crops (Jouan et al., 2019, 2020).

2.2. Growing grain legumes: A farm-specific adoption decision subject to market access

The introduction of a new crop into an existing agricultural production system represents a complex optimisation challenge for each farm. In addition to the pursuit of profit, which is subject to risk and uncertainty, the decision-making process must also consider the maximisation of utility and the constraints imposed by the alternative time horizons involved. Additionally, market-based incentives play an important role in this decision-making process, e.g. in terms of market access and economically viable price signals (Perosa et al., 2021). The absence or inadequate accessibility to markets, such as a lack of transportation infrastructure or asymmetric information, represents a significant obstacle to the decision-making process regarding crop diversification in the agricultural sector. This ultimately leads to elevated transaction costs and relatively low producer prices. (Meraner et al., 2015).

Efficient market structures may positively affect local adoption decisions in favour of a new crop, e.g. grain legumes. Following Mehdi et al. (2018) the decision of a hypothetical German farmer to grow grain legumes is, therefore, modelled as an adoption decision: The aggregate grain legume adoption in German regions (districts) is considered. In each region r, i = 1,…, N farms are assumed to be potential grain legume producers. However, in relation to the research questions it is expected that this maximum area of grain legumes in region r is not necessarily fully utilized by the N farms. Instead, each farmer i individually decides whether to grow grain legumes on a certain number of hectares A in region r. This decision is an adoption function, which can be characterised as:

$$A_{ri} = f(\boldsymbol{F_{ri}}, \boldsymbol{M_{ri}}) \tag{1}$$

where $\boldsymbol{F_{ri}}$ is a vector of farm-specific factors that affect the opportunity costs of grain legume production on farm i in region r, and $\boldsymbol{M_{ri}}$ describes the farm specific market situation for grain legumes including the spatial market structure in region r.

The aggregate adoption decisions by all farms $\sum_{i=1}^{N} A_{ri} = A_r$ regarding a crop or technology are often labelled as the diffusion rate D. The following relation therefore describes the diffusion rate D_r of grain legumes in region r:

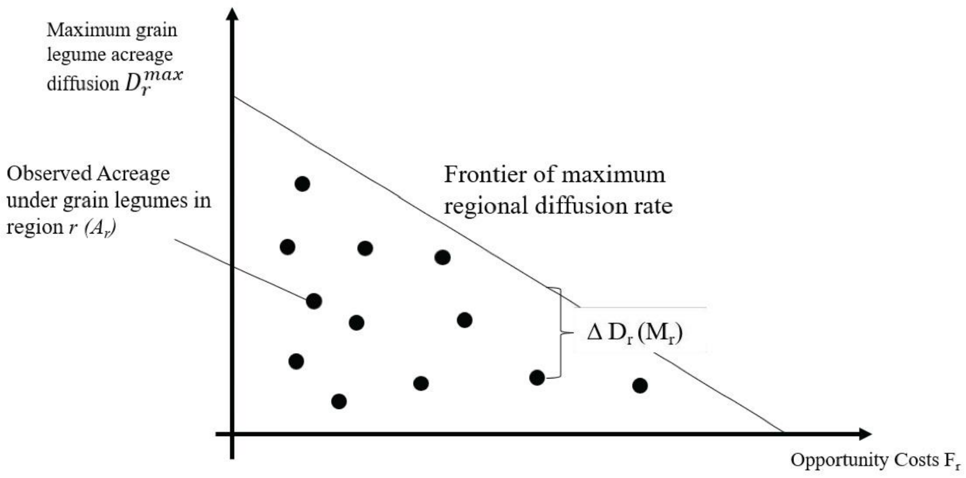
$$D_r = \frac{A_r(\boldsymbol{F_r}, \boldsymbol{M_r})}{A_r^{max}(\boldsymbol{F_r^{min}}, \boldsymbol{M_r^{opt}})} \tag{2}$$

A_r^{max} describes the maximum acreage of grain legumes in region r based on the aggregate minimal opportunity cost of the N farms growing grain legumes $\boldsymbol{F_r^{min}}$ and optimal market conditions $\boldsymbol{M_r^{opt}}$ for the N farms in r.

However, conditional upon the characteristics of $\boldsymbol{F_r}, \boldsymbol{M_r}$ the actually cultivated area $A_r \leq A_r^{max}$. Therefore, the observed diffusion rate D_r in region r is potentially below the corresponding maximum diffusion rate in this region, D_r^{max}.

Figure 2 illustrates the assumed relationship between maximum grain legume acreage diffusion D_r^{max} and regional opportunity cost of grain legume cultivation $\boldsymbol{F_r}$. Figure 2 now introduces the effect of the regional market structure $\boldsymbol{M_r}$ as a downward deviation from the maximum diffusion rate D_r^{max}.

Figure 2: Regional adoption frontier of growing grain legumes



Source: own representation

The intuition behind this figure captures the assumed two-step decision process on farms: First, the farmer decides upon the acreage of grain legumes based on farm characteristics such as soil, climate, other crops and other income-generating activities (animal production, forestry, etc.). Next, the farmer evaluates the prospects for marketing these grain legumes. Less than optimal marketing structures may induce the farmer to further reduce the planted grain legume acreage. This results in a difference Δ between maximum diffusion rate D_r^{max} along the hypothetical diffusion frontier depicted in Figure 2 and the observed diffusion rate D_r.

These considerations lead to the following hypotheses:

H_0 = The regional diffusion rate regarding the acreage under grain legumes does not depend on the regional market environment.

H_A = An improved market environment in region *r* in terms of prices, contract conditions and the regional density of traders, results in a diffusion rate closer to the maximum diffusion rate for that region, $\Delta D_r (M_r)$ declines.

3. Empirical methods and analytical framework

3.1 Empirical Implementation and Data

An empirical implementation of the model outlined in Equation (2) is developed to evaluate the influence of farm-specific characteristics and regional market conditions on the diffusion of grain legume cultivation across different regions in Germany. The model considers both factor groups ($\boldsymbol{F_r}, \boldsymbol{M_r}$) to estimate the maximum potential area for grain legume cultivation.

As described in Section 2.1 the comparatively low acreage of grain legumes in Germany is expected to be explained either by local- and farm specific opportunity cost, or by the regional structure of market access for grain legumes. For empirical implementation both factors are proxied by the variables described in Table 1.

Table 1: Summary statistics of variables used in the empirical implementation

		Minimum	Median	Mean	Maximum
Dependent variable(s)	Legume area (ha/district)	0	216	538	8952
	Area peas (ha/district)	0	44	209	8731
	Area beans (ha/district)	0	28	136	1728
	Area lupins (ha/district)	0	0	48	1727
	Area soybeans (ha/district)	0	0	79	1286
Farm specific factors F_r	Area (ha/district)	32	6090	9074	70729
	Cultivability	0	0.9572	0.8022	1
	eco_share (%)	0.0002	0.0925	0.1035	0.4747
	Livestock density (livestock units/district)	0	15906	30254	357955
Market structure M_r	Legumes traders (count/district)	0	0	0.5	7

Source: own calculation

The data employed in this analysis primarily originates from the 2020 Agricultural Structure Survey conducted by the Statistisches Bundesamt (2023). The dataset includes information on total cultivated area, grain legume acreage and the acreage of competitive crops. The analysis covers 400 German districts, comprising approximately 12.2 million hectares of arable land, with grain legumes cultivated on 216,000 hectares.

Farm- and farmer-specific characteristics $\boldsymbol{F_r}$, have been approximated through region-specific agronomic characteristics, e.g. the agronomic cultivability of grain legumes in region *r*. To account for the specific agronomic requirements of grain legumes, the suitability of land for cultivating these crops was derived from a map created by Roßberg and Recknagel (2017) which outlines regions in Germany that are suitable for soybean cultivation. Although these legumes may differ somewhat in their growing conditions, they are very similar when it comes to their use as animal feed. According to Jezierny et al. (2010) grain legumes like soybeans and others can effectively substitute for each other as feed. Therefore, since soybeans share comparable agronomic needs with other grain legumes, this map provides a reliable indication of the potential for cultivating various legume crops (Watson et al., 2017). This data has been refined by estimating the proportion of arable land in each district suitable for legume cultivation, while accounting for crop-rotation constraints. To account for this adjustment, 'area' is 30 % of a district's arable area (based on Böhm et al. (2020)) that can be used to grow grain legumes under crop rotation restrictions.

Likewise, the proportion of the area cultivated organically per district (eco_share) was considered as a variable, since the cultivation of grain legumes in organic farming is hugely important for diversifying crop rotations.

Additionally, district-specific livestock density was used as a regressor due to the predominant farm-internal use of domestically grown grain legumes in animal feed as opposed to their sale to agricultural traders (Kezeya Sepngang, Stauss, et al., 2018). Nevertheless, most of the protein in Germany is used for fattening pigs, poultry, or beef cattle in animal husbandry-intensive regions (Soisontes et al., 2023). Therefore, it can be assumed that the regional livestock density influences the area currently cropped with grain legumes in the region itself and in neighbouring regions.

Market-specific characteristics $\boldsymbol{M_r}$, have been approximated through specific market conditions in region r.

Due to the non-transparent nature of price formation and contract characteristics in grain legume trading, as noted in prior research (Kezeya Sepngang et al., 2019; Mittag & Hess, 2025), direct data on prices and contract terms are unavailable. Consequently, the spatial distribution of the locations of agricultural traders who buy grain legumes in Germany was used as an approximation for market structure. These locations were taken from the UFOP customer map for grain legumes (Union zur Förderung von Oel-und Proteinpflanzen e.V., 2025), on which agricultural traders who buy grain legumes produced in the respective region can be registered to increase market transparency, as mentioned in Kezeya Sepngang, Stauss, et al. (2018) in the context of inefficient trading structures.

The map of buyers shown in Figure 1 offers an overview of agricultural traders in Germany who have committed themselves to buying grain legumes cultivated both conventionally and organically. It is evident that the trading companies are not distributed evenly throughout Germany and spatial clusters can be identified, which indicates a greater trade/purchase of grain legumes in those regions (Bublik et al., 2025).

It should be noted that the listing of agricultural traders on the buyer map is voluntary and is done on the initiative of the agricultural traders themselves, thus no claim is made that the map is as reliable as (in this case non-existent) official statistics would be. Consequently, the number of agricultural traders per district interested in buying grain legumes is included as a variable in the (spatial) stochastic frontier analysis.

3.2 Spatial stochastic frontier analysis and efficiency

The stochastic frontier analysis (SFA) method was employed to test the hypothesis of an efficient market for grain legumes in Germany. In this context, market efficiency is interpreted as the relationship between regional grain legume cultivation and regional sales structures. For a detailed overview of the SFA approach see Kumbhakar and Lovell (2000) and the recent review by Kumbhakar et al. (2020). In brief, SFA estimates production or cost functions considering potential inefficiency at the firm or regional level (Battese & Coelli, 1995).

The choice of a stochastic frontier model is motivated by the need to establish a theoretical benchmark for the maximum potential acreage under grain legumes that a region could achieve, given its agronomic conditions and resource endowments. Although land use decisions are influenced by market, institutional, and behavioural factors, they remain constrained by biophysical and agronomic limits. The frontier represents this maximum achievable legume cultivation and serves as a yardstick against which observed cultivation levels can be evaluated.

Deviations from this frontier are interpreted not solely as inefficiency but as an aggregate measure capturing various barriers, including limited market access, contract conditions, institutional constraints, and farmer adaptation behaviour. This approach allows a detailed understanding of how grain legume cultivation propagates across various regions.

In the subsequent analysis, the estimated frontier function represents the maximum regional diffusion of grain legume cultivation, i.e., the maximum expected diffusion given regional conditions (see Section 2.2).

Standard practice when performing SFA is to take logarithm of the output variable and fit a likelihood-based model (Kumbhakar & Lovell, 2000; Lai & Kumbhakar, 2020). The logarithm of the absolute planted area under grain legumes A_r in region *r* is used as the dependent variable, including the maximum possible cultivation area $\boldsymbol{A_r^{max}}$ as an explanatory variable in the factor group $\boldsymbol{F_r}$.

Therefore, equation (3), according to Kumbhakar and Lovell (2000), specifies the acreage A_r as a parametric function *f* of $\boldsymbol{F_r}$ *and* $\boldsymbol{M_r}$.

$$A_r = f(\boldsymbol{F_r}, \boldsymbol{M_r}; \beta) + v_r - u_r \tag{3}$$

,where v_r is usually assumed to be normally distributed with mean zero and a constant variance σ^2 , while u_r follows a half-normal distribution (Battese & Coelli, 1995). In the presence of spatial dependencies, e.g. due to autocorrelation among farms or regions, the assumption that v_r is independent is violated. This spatial autocorrelation can bias estimation results in two ways: firstly, it can lead to incorrect inferences about parameter estimates, similar to autocorrelation in time series data; secondly, severe autocorrelation may induce correlation between explanatory variables and error terms, causing biased and inconsistent estimates (Anselin, 2002). Spatial econometric methods provide tools to address these issues by explicitly modeling spatial patterns in the data.

Although often neglected in studies of market access and competition in agricultural markets (Graubner et al., 2011), the spatial dimension plays a crucial role in explaining land-use decisions. For instance, farmers' adoption of grain legumes may be influenced by neighbouring regions through the diffusion of knowledge, peer effects, or shared infrastructure (Cardamone, 2020). Ignoring such spatial dependencies in stochastic frontier models can reduce statistical efficiency and bias parameter estimates (Orea & Álvarez, 2019). To capture these spillovers and contextual effects, a spatial weights matrix (SWM) is incorporated into the model framework.

The data-driven approach by Bauman et al. (2018) was implemented to select the most appropriate SWM. A distance-based spatial weights matrix with a 70 km threshold was identified as the best-fitting spatial structure based on model diagnostics and goodness-of-fit criteria. This narrow threshold ensures that only geographically close regions are treated as neighbours, avoiding oversmoothing effects and better reflecting localized market dynamics. The choice of a 70 km radius is based on both theoretical and empirical considerations. From a theoretical perspective, agronomic interactions such as knowledge transfer, market access, and environmental spillovers tend to operate over relatively short distances (Foster & Rosenzweig, 1995). Regional cooperation between farmers and traders typically occurs within a realistic commuting or distribution range beyond which transaction and coordination costs rise significantly. Furthermore, natural conditions relevant to legume cultivation (e.g. soil and climate) are more homogeneous within this radius. Empirically, the 70 km matrix demonstrated superior model performance (e.g., higher adjusted R^2, lower AIC, and reduced residual spatial autocorrelation) compared to alternative matrices (e.g., with 100 km, 300 km, Gabriel graph, or Delaunay triangulation), and was therefore selected as the main specification. Alternative matrices were tested as robustness checks and are presented in Appendix A.

In the selected spatial weights matrix W_{rs} a binary structure is used: district *r* receives a nonzero weight for district *s* if *s* lies within a 70 km radius, and zero otherwise. Self-neighbourhood is excluded, so that $w_{rr} = 0$.

$$W_{rs} = \begin{bmatrix} 0 & \cdots & w_{1,N} \\ \vdots & \ddots & \vdots \\ w_{N,1} & \cdots & 0 \end{bmatrix}$$

All neighbours are weighted equally within this radius; inverse-distance or decay-based weights were not applied, as our primary aim was to capture regional market presence rather than gradational spatial influence.

Based on this spatial structure, the spatial stochastic frontier model (sSFA) was estimated as proposed by Barrios and Lavado (2010):

$$A_r = f(\boldsymbol{F_r}, \boldsymbol{M_r}; \beta) + \delta\, W_{rs}[A_r - f(\boldsymbol{F_r}, \boldsymbol{M_r}; \beta)] + v_r - u_r$$

Here, A_r is the observed grain legume acreage in district r, $f(\boldsymbol{F_r}, \boldsymbol{M_r}; \beta)$ is the parametric frontier function estimated from farm-specific ($\boldsymbol{F_r}$) and market-specific ($\boldsymbol{M_r}$) characteristics, and δ captures spatial dependence between residuals in neighbouring regions. The composed error term consists of a symmetric stochastic noise component $v_r \sim N(0, \sigma^2)$ and an inefficiency component $u_r \sim |N(0, \sigma^2)|$ assumed to follow a half-normal distribution (Battese & Coelli, 1995).

This spatial specification allows to interpret the inefficiency term u_r as a composite of three sources: (1) spatial inefficiencies related to a region's context and its neighbours, (2) structural inefficiencies due to limitations in the explanatory variables, and (3) random noise. The sSFA was estimated using the ssfa package in R (Fusco & Vidoli, 2022) while construction and testing of spatial weights matrices were performed with the spdep package (Bivand, 2022).

4. Results

First, two distance-based spatial weights matrices W_{rs} were created using a threshold of 70 km and 100 km. Although the approach by Bauman et al. (2018) recommended a threshold of 70 km as most suitable, a SWM with a threshold of 100 km was included as a robustness check. For smaller thresholds, empty neighbour sets were found, and thus, no matrix was created. The connectivity statistics are shown in Table 2.

Table 2: Connectivity statistics of spatial weights matrix

	d = 70 km	d = 100 km
Number of regions	400	400
Number of non-zero links	7094	13432
Percentage non-zero weights	4.4338	8.3950
Average number of links	17.735	33.580

Least connected region (... links)	2	3
Most connected region (... links)	38	59

Source: own calculation

The greater the distance at which neighbouring regions are assigned a weight, the greater the average number of links; the shorter the distance, the higher the percentage of zero weights. Low connectivity can be interpreted as low economic interaction between the respective regions; for example, farmers would not consider selling legumes to a trader in an unconnected region. The two distances present different assumptions about the geographical range farmers would consider selling legumes to traders (see introduction).

In estimating the SFA and the sSFA, the dependent variable ‘area currently cropped with grain legumes (= legume area)’ was logged, and a log-lin function was estimated.

Table 3 shows the results of the ‘regular’ (= non-spatial) stochastic frontier analysis. When spatial dependencies are not accounted for in the SFA, only the area available for cultivating grain legumes remains significantly associated with the area currently cropped with grain legumes.

Table 3: Results of the stochastic frontier analysis

	SFA		
	Coefficient	Std. error	p-value
Intercept	2.5445	0.1016	< 0.0000
Area (ha) / 1000	0.0543	0.0051	< 0.0000
Cultivability (%)	-0.0839	0.0892	0.3472
Legume traders (count)	0.0583	0.0310	0.0599
eco_share (%)	0.7575	0.3732	0.0424
Livestock density (LU) /1000	0.0001	0.0001	0.2526
σ^2	1.8176	0.1234	< 0.0000
γ	0.9956	0.0025	< 0.0000

Mean efficiency	0.4860
AIC	871.4842
Log-likelihood	- 427.7394

Source: Own Calculation; n=400

While eco_share and the available agricultural area were significantly associated with grain legume acreage, the number of legume traders was only marginally associated with it, whereas cultivability showed no statistically significant association. Additionally, the validity of using the stochastic frontier and its dominance over the simple regression must be checked. The γ-statistic value for the model in Table 3 is close to 1 (significantly higher than 0), so the presence of inefficiency in the data was observed, and the stochastic frontier models were preferred over a simple regression. A mean efficiency of 0.4860 was estimated, while stochastic and structural components decreased efficiency significantly. Additionally, the Moran's I test for the classic SFA model shows significant spatial autocorrelation of the residuals (p <0,000), recommending the use of a spatial frontier model.

Table 4 presents the results of the estimated spatial stochastic frontier models. Distance-based weights matrices with 70 km and 100 km were incorporated into the model. SSFA-Models incorporating other SWMs have been estimated as robustness checks and are available from the authors upon reasonable request.

Table 4: Results of the spatial stochastic frontier analysis for grain legumes

	sSFA (d = 70 km)			**sSFA (d = 100 km)**		
	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value
Intercept	2.6238	0.1118	< 0.0000	2.5022	0.1031	< 0.0000
Area (ha) / 1000	0.0537	0.0055	< 0.0000	0.0544	0.0054	< 0.0000
Cultivability (%)	-0.0642	0.0821	0.4472	-0.0891	0.0813	0.2732
Legume traders (count)	0.0558	0.0267	0.0365	0.0570	0.0278	0.0403
eco_share (%)	0.5877	0.3849	0.1268	0.8369	0.3568	0.0190
Livestock density (LU) /1000	0.0016	0.0014	0.2422	- 0.0001	0.0013	0.4168

σ_u^2_DMU	1.7818	0.1403	< 0.0000	1.8137	0.1429	< 0.0000
σ_v^2	0.0078	0.0039	0.0421	0.0070	0.0039	0.0730
ρ	0.0036			-0.0011		
γ	0.9910			0.9940		
λ	227.16			260.50		
Moran's I	0.0655			0.0408		
Mean efficiency	0.4882			0.4842		
AIC	887.9824			890.8625		
Log-likelihood	-425.9912			-427.4312		
Likelihood-Ratio-Test (vs. OLS)	164.004 (p-value < 0 0001)			161.124 (p-value < 0 0001)		

Source: own calculation; n=400

Overall, both models yield consistent coefficient estimates and confirm the presence of significant inefficiency effects.

Available agricultural area (in 1,000 ha) is consistently positively and significantly associated with the area under grain legumes. Similarly, the number of legume traders is positively and significantly associated in both models, with a slightly larger coefficient in the 100 km specification. The share of organically managed land ("eco_share") is significantly associated with grain legume acreage only in the 100 km model ($p = 0.019$), pointing to potential spatial sensitivity in ecological practices. By contrast, cultivability and livestock density are not significantly associated with grain legume acreage in either model, suggesting that these factors are less relevant for explaining differences in the extent of legume cultivation.

The inefficiency variance component (σu^2_DMU) is large and highly significant, indicating the presence of substantial inefficiency. The noise variance (σv^2) is relatively small but statistically significant in the 70 km model and marginally so in the 100 km model. The lambda statistic (λ), the ratio of inefficiency to noise, reaches very high values (227.16 and 260.50), underlining the dominant role of inefficiency in explaining deviations from the frontier.

Regarding the spatial structure, the spatial autoregressive parameter (ρ) is close to zero in both models (0.0036 and –0.0011), and Moran's I statistics (0.0655 and 0.0408) indicate very weak residual spatial dependence. Although the spatial autoregressive parameter (ρ) is small, this does not imply the absence of spatial dependence. Rather, it suggests that the spatial structure is likely already captured by the model components, particularly the spatial weight matrix and the inefficiency term. This interpretation is supported by the substantial improvement in model fit compared to the non-spatial SFA model and the significant spatial autocorrelation in the residuals of the SFA (Moran's I test, $p < 0.0001$), which is notably reduced in the sSFA framework. These findings indicate that failing to account for spatial dependence in the SFA leads to spatially correlated inefficiency or unobserved heterogeneity, which the sSFA is able to absorb even when the explicit spatial parameter estimate remains small.

Mean efficiency is similar in both models (0.4882 and 0.4842), suggesting moderate overall efficiency levels in the sample.

Likelihood-ratio tests clearly reject the null hypothesis of no inefficiency ($\sigma_u^2 = 0$) in both cases ($p < 0.0001$), and both spatial models exhibit substantially better fit than the corresponding OLS model, as evidenced by lower AIC values (887.98 and 890.86, respectively).

A summary of the efficiencies estimated in the different models is presented in Table 5.

Table 5: Summary statistics of the estimated efficiencies

	SFA	**sSFA (d = 70 km)**	**sSFA (d = 100 km)**
Minimum	0.0346	0.0348	0.0343
Median	0.5312	0.5414	0.5318
Mean	0.4860	0.4882	0.4842
Maximum	0.9641	0.9632	0.9644

Source: own calculation

Differences in the models' efficiency estimates should not be analysed directly because efficiency estimates of different model specifications are generally non-comparable. Efficiency values, therefore, allow conclusions to be drawn about the patterns of the efficiency estimates, not about the numbers themselves. Additionally, mean efficiency scores show that regions operate well below the estimated adoption frontier. However, the inefficiency term does not reflect a single mechanism or pure inefficiency in a strict sense. Rather, it reflects unrealised diffusion relative to comparable regions, conditional on observed characteristics, and may capture unobserved adoption barriers. These include structural constraints (e.g. limited storage, processing, or trading infrastructure) as well as heterogeneity in crop rotations, farm structure, profitability, and farmers' knowledge or preferences. With district-level data, these factors cannot be empirically disentangled.

5. Discussion

Agricultural traders interested in buying grain legumes are unevenly distributed across Germany, potentially indicating regional market and cultivation inefficiencies. However, the identification of traders is based on a buyer map that relies on voluntary registration. Hence, the dataset may therefore provide an incomplete picture of regional market structure and may introduce measurement error into the market access variable, although there is no clear indication that unregistered traders differ systematically from registered ones. The issue is therefore primarily one of incomplete coverage rather than substantial selection bias. Despite this, it remains the only nationwide dataset available and provides the best basis for analysis.

Another potential concern is that the number of registered legume traders may be endogenous to cultivation patterns, weakening causal interpretation. However, several contextual factors suggest that endogeneity is likely limited: Trader locations in Germany reflect long-established regional trading structures and entry involves high fixed costs and long-term planning rather than short-term responses to fluctuations in legume cultivation. Trading decisions are alsostrategic and embedded within broader crop-marketing portfolios, suggesting distribution is largely exogenous to short-run variation in legume acreage. Nonetheless, results are interpreted cautiously as there is a literature gap regarding the adoption of a comprehensive approach capable of dealing with endogeneity in SFA (Russo et al., 2023) and further research with stronger identification strategies or longitudinal data is needed.

Spatial analyses shows that the presence of grain legume traders is positively and significantly associated with the decision to cultivate grain legumes and, hence, cultivation efficiency. This robust result highlights the importance of regional trading structures for legume adoption across both spatial specifications. The hypothesis that an improved market environment regarding trading structures results in greater adoption and, thus, a higher diffusion rate cannot be rejected.

The available agricultural area is significantly positive, confirming that larger land availability is associated with higher legumes adoption. In contrast, cultivability and livestock density are not statistically significantly associated with legume cultivation in the models, indicating that market access and land endowment matter more than agronomic suitability. Since legumes can be grown widely across Germany (Roßberg & Recknagel, 2017; Stephenson, 2022), cultivability is not a binding constraint and likely affects decisions mainly through opportunity costs rather than direct suitability. Land with more favourable soil conditions is often used for crops with higher expected returns.

The share of land under organic farming (eco_share) is positvely associated with grain legume area, though only significant in the 100 km model, indicating stronger effects at broader spatial scales. This reflects the role of crop rotations in organic systems, where legumes support weed control and soil fertility through nitrogen fixation (Preissel et al., 2015). Subsequent crops benefit agronomically from the preceding legume cultivation (Bedoussac et al., 2015). As organic farmland is expected to increase in the next few decades, legume cultivation may increase accordingly (Statistisches Bundesamt, 2021). Apart from this, spatial dependencies have been reported in regions with high shares of organic farming: such regions tend to be close to others with a high proportion of organically farmed land, and thus external scale economies seem to exist (Bonfiglio & Arzeni, 2020). Together with the positive effect of the large share of organic farming, these spatial dependencies may increase the acreage of grain legumes in future.

Considering the distance-based weights matrix and spatial dependencies, positive spillover effects between the districts are shown. Here, the diffusion rate of growing grain legumes is positively influenced by the presence of agricultural traders in the local area.

Building on this, the estimated gap between maximum feasible and observed diffusion should be interpreted cautiously. It does not solely reflect inefficiency but may capture unobserved regional differences, such as farmer preferences, risk attitudes, farm structures, and crop rotations, which cannot be assessed with county-level data. However, they cannot be analysed directly with the available county-level data. A more precise assessment of these factors would require detailed farm-level data, which are beyond the scope of thisstudy and represent an area for future research. Similarly, unobserved differences in the relative profitability of grain legumes across regions may contribute to the estimated gap, since detailed farm-level information on crop-specific revenues, costs, and hence opportunity costs is not available. In contrast, path dependencies appear less likely to arise at the farm level, as grain legume cultivation typically does not require asset-specific investment in specialised machinery or equipment. Instead, persistence effects could plausibly be linked to downstream processing and trading structures. Overall, the gap reflects unrealised diffusion potential relative to comparable regions rather than strict inefficiency.

The choice of a distance-based spatial weights matrix (SWM) is debatable, as its assumed structure may not reflect reality, which is a common issue in spatial modelling.(Bhattacharjee & Jensen-Butler, 2013). Mur et al. (2012) provide an overview of the criteria that should be considered when choosing a suitable spatial weights matrix, given that considerable uncertainty surrounds the choice of appropriate distance measures in many applications (Anselin, 2002; Harris et al., 2011). Using the data-driven approach of Bauman et al. (2018) a distance-based SWM with a 70 km threshold was selected as the preferred spatial structure. This specification minimized residual spatial autocorrelation and suggests that spatial interdependencies are mainly local, aligning estimated effects with observed data patterns. (see also Section 3.2). However, a data-driven selection may reflect sample-specific patterns, risking overfitting and limited generalizability. The approach may overlook theoretically plausible interactions at larger scales, such as long-distance trade or knowledge spillovers beyond the 70 km threshold. Therefore, it should be complemented by theoretical considerations and robustness checks, as done here by testing alternative matrices and thresholds. A 70 km threshold is also theoretically plausible, as agronomic, market, and environmental interactions are typically local.

All in all, the findings suggest that policies aimed at increasing grain legume cultivation should go beyond farm-level production incentives, which is in line with Kremmydas et al. (2024) . As market access and regional trading structures are key, measures should address value chain bottlenecks, including support for regional processing and trading structures, better coordination coordination between farmers, traders, and processors, and improved market transparency. At the European level, these results highlight the importance of embedding grain legumes more strongly in CAP eco-schemes, rural development measures, and wider protein strategies. Targeted support for legume value chains in regions with limited market access could reduce structural barriers to adoption more effectively than area-based incentives alone and strengthen the competitiveness of grain legumes.

6. Conclusion

There is a high demand for domestic grain legumes as a protein-rich component in German animal feed while domestic production cannot meet market demand. Even though grain legumes additionally contribute to resilient and biodiverse production systems, the development of acreage and thus of production volumes has fluctuated considerably around low absolute numbers for years. Therefore, this paper investigated the factors that influence the adoption decision and diffusion rate regarding the cultivation of grain legumes, focusing on the structure of the German market for grain legumes. Using spatial stochastic frontier analysis, the spatial distribution of agricultural traders is examined in relation to the potential diffusion of grain legume cultivation in terms of acreage and production. This analysis found that the number of agricultural traders in a region is positively associated with the utilisation of land potentially suitable for grain legume cultivation. The spatial distribution of agricultural traders can be interpreted as an indication of market access influencing crop diversification decisions and, thus, land use change. Consequently, the hypothesis that improved trading structures are associated with an increase in adoption and diffusion cannot be rejected. Establishing improved trading structures could lead to a higher diffusion rate and thus to more efficient utilisation of cultivated land for grain legumes and, hence, protein production. This could be achieved, for example, by establishing networks and cooperatives among farmers to pool production quantities and coordinate marketing beyond the local area.

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Appendix

Table A: Quality Parameters of selected SWMs (according to Bauman et al. (2018))

Rank	Matrix	Adj. R^2	p-value	No. of variables included	Adj. R^2 (selected)
1	Dnear70000_Binary	0.4683	0.0012	37	0.4613
2	Dnear70000_Up_0.5	0.4458	0.0012	31	0.4228
3	Dnear70000_Down_5	0.4308	0.0012	26	0.4264
4	Delaunay_Down_5	0.3154	0.0012	15	0.3069
5	Delaunay_Binary	0.3145	0.0012	15	0.3120
6	Delaunay_Up_0.5	0.3062	0.0012	24	0.3053
7	Gabriel_Down_5	0.2988	0.0012	18	0.2926
8	Gabriel_Binary	0.2682	0.0072	14	0.2635
9	Relative_Binary	0.2671	0.0167	17	0.2622
10	Relative_Down_5	0.2523	0.0202	16	0.2492
11	Relative_Up_0.5	0.2461	0.0273	14	0.2457
12	Gabriel_Up_0.5	0.2433	0.0202	13	0.2342

Source: Own calculation. “Dnear” = distance-based SWM with distance in meters; “Delaunay” = neighborhood based on Delaunay triangulation; “Gabriel” = neighborhood based on Gabriel graph; “Relative” = neighborhood based on Relative Neighborhood graph; “Binary” = 0/1 contiguity weights; Down_5 = distance-decaying weights; “Up_0.5” = distance-upweighting weights. Adj. R^2 (selected) =Adjusted R^2 of the best-performing model specification selected for each spatial weight matrix according to the procedure of Bauman et al. (2018)