Public spending for agricultural risk management: land use, regional welfare and intra-subsidy substitution

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Abstract: This paper analyses the factors influencing public expenditure on the EU's Risk Management Toolkit comparing six types of regional-level spatial autoregressive models, and finding that there is a predominance of socio-economic factors over risk and agro-ecological factors in the allocation of budget. Higher expenditure occurs in more affluent regions and in areas with clusters of relatively high welfare. Conversely, regions with high agricultural value added and a greater presence of permanent crops spend less on the Risk Management Toolkit, indicating a trade-off with private risk management products (e.g. insurance) and on-farm practices. A higher intensity of CAP subsidies tends to reduce expenditure on the Risk Management Toolkit, indicating that the income stabilization capacity of direct payments might be an alternative to risk management and indicating a substitution between policies. Moreover, a strong spatial dependence of the regional expenditures indicates a key role of the higher-level institutional environment and political economy processes in the allocation of budget. The paper concludes deriving policy implications for the new CAP reform which is characterized by higher flexibility in deciding what policy instruments to implement at the territorial level.

Key Words: risk management, CAP, spatial analysis, public spending, land use.

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1. Introduction

Farming faces a wider variety of risks in comparison with businesses in other sectors, ranging from environmental, market, financial, institutional, and human or personal risks. Such risks are typically dealt with at the individual farm level (De Salvo et al., 2019), with farms adopting different risk management (RM) strategies such as agricultural insurances, production/marketing contracts and derivatives, and production or income diversification (European Commission, 2017). However, the systemic nature of risks means that governments are responsible for retaining farmers in the agricultural sector and for ensuring adequate food supplies. Moreover, the costs associated with risk management (Vigani and Kataghe, 2019), the failures of agricultural insurance markets such as information asymmetries, adverse selection (Enjolras and Sentis, 2011) and moral hazard (Goodwin, 2001), induce farmers to ask for government intervention.

During the period 2014-2020, in the European Union (EU) the policies for agricultural risk management were provided by: i) the Common Market Organisation (CMO) of the Common Agricultural Policy (CAP), covering specifically the fruit, vegetables and wine sectors; ii) the Pillar 2 of the CAP (Risk Management Toolkit); and iii) state aids. Public interventions supporting farms are mainly concentrated in the CAP. The direct payments introduced since the 2003 CAP reform provide farmers with overall income support, but since the 2013 CAP reform specific measures for risk management can be introduced by EU Member States (MS) and regions in their Rural Development Programmes (RDP). These are Measure 5 (M5) on "*Restoring agricultural production potential damaged by natural disasters and catastrophic events and introduction of appropriate prevention actions*" and Measure 17 (M17) on "*Risk management*", together constituting the so-called Risk Management Toolkit (RMT).

Although farmers generally welcomed the support for risk management, the RMT was not as successful as expected in the EU excluded a few MSs. Only 59 RDPs from twelve MS have adopted the RMT, and only 387 regions of the Nomenclature of Territorial Units for Statistics level 3 (NUTS3) [1] have disbursed the expenditure with about 1.5% of the total rural development budget programmed over 2014-2020. The RMT is a voluntary policy, therefore EU MSs had flexibility in its application and implementation. Each MS adopted a specific strategy in combining the financial support options considered in the CAP, prioritising some instruments over others. This responds to the past experience of each MS in using some instruments (European Commission, 2017; Rippo and Cerroni, 2022), the culture and traditions among farmers and the competitiveness and innovation of the private sector – i.e. banking, insuring and financing – in promoting them (Cafiero et al., 2007).

[1] According to the Regulation (EC) No 1059/2003, the size of NUTS3 regions correspond to administrative units with population between 150,000-800,000 inhabitants.

Given the low rate of public expenditure on a tool that potentially can improve the stability and resilience of agricultural and food production, the aim of this paper is to investigate the factors affecting EU regions' expenditure towards the RMT and to identify the potential reasons for the (relative) low voluntary adoption in certain regions and the success of the RMT in other regions. The academic literature includes numerous detailed studies on the drivers of farm-level adoption of RM tools (e.g. Goodwin, 1993; Mishra and Goodwin, 2006; Finger and Lehmann, 2012; Enjolras and Sentis, 2011; Jensen et al., 2018), their effects on farmers' production decisions (e.g. Claassen et al., 2016; Yu et al., 2018; Shi et al., 2019) and on welfare (e.g. Smith et al., 2016; Lusk, 2017; Du et al., 2017), but analyses of the decision-making processes and explanatory factors of public expenditure on RM are still few in number. Understanding how budget is allocated across different policies can help design targeted policies to mitigate agricultural risks and improve their implementation at the local level. The literature of reference for this research relates to the drivers of CAP expenditure (see Section 3 for a review of this literature). This literature is rather small but important as it provides empirical evidence with direct relevance for public policies. However, it is quite broad in scope when considering the entire EU / CAP expenditure and uses proxies instead of observed data, such as indices of expenditure intensity (Camaioni et al., 2016) or funds allocation intentions (Crescenzi et al., 2015; Zaporozhets et al., 2016).

We contribute to this literature by studying a specific CAP instrument, the RMT, by using regional-level data of actual ex-post European Agricultural Fund for Rural Development (EAFRD) expenditure on the RMT, taken from the European Commission's (EC) Clearance Audit Trail System (CATS). To the best of our knowledge, this is the first time this data source has been used for researching the EU regions' public expenditure. We analyse three main factors that, according to literature, have a role in national or local government decision-making on expenditure for RM policies; namely socio-economic, risk, and agro-ecological factors. Because expenditure decisions, climate and farming systems characteristics might cross the boundaries of individual decision-making units (e.g. the same RDP might be applied to multiple regions), these factors are analysed with six different spatial autoregressive models. There are three different types of spatial interactions which can cause spatial effects or spatial autocorrelation in budget allocation: 1) an endogenous effect, where the observed expenditure in one spatial unit correlates with the expenditure of other neighbouring spatial units; 2) an exogenous effect, where the observed expenditure correlates with the factors affecting the expenditure of other neighbouring spatial units; and 3) a correlated effect, where the expenditure of different spatial units are correlated due to unobserved characteristics.

The results suggest that higher expenditure for the RMT is related mainly to socio-economic factors and to the local and higher-level (national or EU level) institutional environment determined by political economy processes, such as lobbying activities and political decisions. The more economically developed EU regions in terms of gross value added (GVA) per capita tend to spend more towards the

RMT. On the contrary, regions which are characterized by higher agricultural value added (i.e they have a higher proportion of land area for permanent crops and distribute more direct and rural development subsidies compared to the size of the agriculture sector) spend less towards the RMT. This indicates a certain degree of substitution between risk management policies and direct payments. Moreover, we find a strong spatial dependence across regions. The high spatial dependence indicates the influence of political institutions, farmers' culture and traditions towards risk management, and the competitiveness and innovation of the private sector (e.g. banking, insuring and financing). The effect of the spatial dependence also indicates the influence of environmental and climatic factors, and it is predominant with respect to direct effects due to drought, rain and floods.

2. Literature review

Academic literature on the adoption of agricultural RM tools has grown significantly since the 90s, following the launch of the Federal Crop Insurance Act of 1980 in the US, and further accelerated in the 2000s with the development of agricultural RM in the EU and the global diffusion of index-based insurances.

A significant proportion of this literature was focussed on the determinants of adoption of agricultural insurances. Early studies (e.g. Chambers, 1989; Goodwin, 1993; Smith and Goodwin, 1996; Just et al., 1999) demonstrated that moral hazard, adverse selection and asymmetric information are three major reasons explaining the (poor) availability of agricultural insurance products on the market, justifying public policy interventions. The adoption of crop and revenue insurance of farms has been widely studied in North America (e.g., Coble et al., 1996; Mishra and Goodwin, 2003 and 2006; Sherrick et al., 2004; Velandia et al., 2009; Roznik et al., 2019) and in Europe (e.g. Garrido and Zilberman, 2008 for Spain; Finger and Lehmann, 2012 for Switzerland; Enjolras and Sentis, 2011 for France; Lefebvre et al., 2014 for Bulgaria; Santeramo et al., 2016 for Italy; Was and Kobus, 2018 for Poland), while the adoption of index-based insurance has been studied especially in developing countries (e.g. Jensen et al., 2018; Takahashi et al., 2020; Bucheli et al., 2022). These analyses follow expected utility theory or behavioural decision-making models and identify a large set of factors driving the uptake of insurance: farm characteristics (e.g., farm size, crop type) and farmers' attributes (e.g., gender, age, education) (e.g. Enjolras and Sentis, 2011; Santeramo et al., 2016; Jensen et al., 2018; Bucheli et al., 2022;); farmer's risk attitude and risk perception (e.g. Hellerstein et al., 2013; Menapace et al., 2013); alternative coping tools such as farm diversification (Enjolras and Sentis, 2011), off-farm income and direct payments (Finger and Lehmann, 2012; Yu and Sumner, 2018) or technology (e.g. Foudi and Erdlenbruch, 2012); expected indemnification (e.g. Liesivaara and Myyrä, 2017; Wąs and Kobus, 2018); previous experience with risks and RM (e.g. Wąs and Kobus, 2018; Santeramo, 2018); and behavioural and psychological factors (e.g. Cao et al., 2019; Dalhaus et al., 2020; Giampietri et al., 2020).

A second important strand of literature studies the effects of public spending supporting agricultural RM. Recent articles have investigated the effects of agricultural insurance programs in developing countries (e.g. Karlan et al., 2014; Budhathoki et al., 2019). Many of these studies use controlled economic experiments of agricultural insurance. For example, Cai et al. (2015) studied a microinsurance program for raising sows in China, finding an increased production of sows which persists in the long-term. Cole et al. (2017) found that the provision of free insurance led to more planting of higher return and higher risk cash crops. Significant articles have analysed the effects of US federal premium subsidies on crop acreage. Among the most recent, Claassen et al. (2016) found that the federal crop revenue insurance programs have significant impacts on land use, crop choice and crop rotation in the U.S. Corn Belt region. Yu et al. (2018) found that a 10% increase in the premium subsidy led to a 0.43% increase in crop acreage, and to an indirect coverage effect. That is, the subsidy induces farms to increase crop insurance coverage, which increases the amount of subsidies obtained by the farm making farm revenue less variable; therefore farms have an incentive to increase the acreage of insured crops. Shi et al. (2019) assessed the effect of the federal crop insurance program on the acreage and yield of major specialty crops in California, showing positive effects for apples, grapes, and dry plums, and negative for walnuts and beans. Other articles have analysed the effects of US federal premium subsidies on welfare. Smith et al. (2016) demonstrate that a large part of the welfare transfer generated by premium subsidies is captured by insurance companies and agents, increasing the spending of the federal government and de-facto subsidizing these companies. Lusk (2017) showed how removing the premium subsidies would have aggregate net economic benefits, with taxpayers being the main beneficiaries *vis-à-vis* farmers, but with a significant variation in welfare effects across states. Du et al. (2017) found that farmers are less likely to choose an insurance product if out-of-pocket premium expenditures increase, despite premiums are subsidized, because farmers place more emphasis on the anticipated gains deriving from avoiding the premium cost rather than on getting a later compensation after a hypothetical loss. This is considered anomalous behaviour because, by renouncing to subsidized insurance, farmers renounce to the income transfer from taxpayers. Finally, some studies argue that insurance subsidies cannot be justified on the basis of the higher riskiness of agricultural businesses, because in the US economy the failure rate of non-farm businesses is higher than that of farm businesses, and the value of insured potential losses in non-agricultural activities is higher than that of agricultural activities (Smith, 2013; Smith and Goodwin, 2013).

In Europe, most of the research efforts on RM policies have been dedicated to the study of the Income Stabilisation Tool (IST) of the CAP, which was planned by three EU MS but activated in only one RD program across the EU MS. For this reason, most of the studies are explorative ex-ante analyses, country- or region-specific, aimed at assessing the economic feasibility, the prospect demand and the potential welfare effects of introducing the IST (e.g., Capitanio et al., 2016; El Benni et al., 2016; Trestini et al., 2018; Severini, et al., 2019; Giampietri et al., 2020; Louhichi and Merisier, 2023). For a detailed review of this literature, see a recent article by Rippo and Cerroni (2022). Rippo and Cerroni (2022), who studied the apple sector in the only region that has operationalised the IST in the EU (the Autonomous Province of Trento in Italy), found that the adoption of the IST is influenced by crop production specialisation in association with greater risk exposure and previous experience with mutual funds. A relevant exception to this literature is the article of Santeramo et al. (2016), which studies farmers' participation in the subsidized insurance market in Italy, showing that the participation rate is higher for large farms, but it is negatively correlated with crop diversification and high premiums. Finally, Popp et al. (2021) conducted a qualitative analysis across OECD Member States to understand whether publicly supported RM tools will gain positive policy feedbacks and policy lock-in (i.e. a situation that makes it difficult to reverse a policy at a later stage) as it happened with traditional farm income support instruments (e.g. direct payments). Their results show that a more intense adoption of RM tools depends on the length of time since the policy has been introduced in the policy mix; the budgetary volume allocated to the policy; lobbying activity; and the availability of alternative policies (e.g. direct payments).

With respect the literature described so far, our study provides several contributions. Firstly, with some notable exceptions (e.g. Finger and Lehmann, 2012; Santeramo et al., 2016), most of the studies listed above ignore the effects of other policies existing in conjunction with the subsidized RM tools (e.g., direct payments, environmental schemes, price or tax policies). In our analysis we consider other CAP instruments which have also income stabilizing effects, potentially overlapping with the RMT. Secondly, most of the European studies have focused exclusively on the IST and not on the whole of the CAP's RM package. The IST is only one element of the RM toolkit, largely unadopted and activated in a single EU region. Therefore, such studies could not make use of actual expenditure data for a broad geographical area and relied on either qualitative assessment of farmers willingness to adopt the IST or quantitative simulations based on secondary data. Our study, however, covers the whole of the RMT, including the IST, using actual expenditure data. Thirdly, the literature tends to focus on farms' adoption of (subsidized) RM, which represent the demand side of public support for RM, but it ignores the supply side. Policymakers' incentives for allocating budget towards RM policies are likely different from the reasons driving farmer demand for such policies, and such incentives are likely of a political economy nature, involving lobbying activities and the outcomes of the balance of power between stakeholders. Therefore, the drivers of diffusion of RM tools also involve "top-down" (from decision makers to users) and not only "bottom-up" mechanisms. Because decision making affects the multitude and not the single individual, an aggregate analysis is required. In our case, we work at NUTS3 regional level, which provides sufficient aggregation for decision making units (regional governments) but is disaggregated enough to take into account differences between RD programs in an EU MS.

In this respect, our study also contributes to a relatively small and recent literature studying the drivers of the CAP expenditure. Crescenzi et al. (2015) analysed the financial allocations of regional, rural development and agricultural policies of the EU in order to assess their impact on territorial cohesion. Looking at the 1994–2013 period, they conclude that the territorial focus of the CAP conflicts with some of the EU cohesion policies. Zaporozhets et al. (2016) examined the determinants of the EU budget allocation in the period 1976 - 2012, identifying two alternative explanations of the EU budget distribution across the MS: i) a "needs view" linked to the principle of solidarity in which MS with a relatively large agricultural sector and a relatively worse economic situation are the major recipients of the EU budget; and ii) the budget allocation reflects the distribution of a MS's political power - thus MS with more power in the allocation process receive larger shares of the budget. Monsalve et al. (2016) studied the sustainability benefits of higher EAFRD spending, finding that MS with higher EAFRD endowments benefitted from higher economic sustainability. Particularly relevant for our study, both in scope and methodology, is the study of Camaioni et al. (2016). For the period 2007-2011, they identify three main drivers of rural development expenditure. Firstly, country-specific drivers are due to systematic differences in rural support across MS. Secondly, the greater the degree of rurality in a region, the more a region will spend on rural development. Lastly, the authors highlighted the importance of spatial drivers in that the influence of bordering regions and their degree of rurality drives regional expenditure on rural development in the target MS. Our study's contribution to this literature is threefold. First, we analyse a comprehensive set of factors affecting public spending that span multiple dimensions and not single ones, such as only rurality or structural disadvantage, while still including proxies for these factors. Second, we use actual expenditure data instead of prospective funds allocation which gives an indication of spending intension but that might not be realized. Third, we cover the whole programming period 2007-2013 providing a full and not partial ex-post view of the factors influencing expenditure.

3. Factors influencing risk intervention

From the literature analysed in the previous section we can identify three groups of factors affecting the adoption of RM tools, namely socio-economic, risk and agro-ecological factors. These groups are corroborated by a stakeholders' consultation conducted by the European Commission (2017) and we use this classification to guide the selection of explanatory variables for the empirical model (see Section 4).

Regarding socio-economic drivers of agricultural RM, at the micro level, farm-related characteristics (e.g. farm size, production practices) and farmers' specific attributes (e.g. gender, age, education, behavioural factors) are generally considered to be key factors explaining the demand for agricultural insurance and mutual funds (Finger and El Benni, 2014; El Benni et al., 2016; Trestini et al., 2018). At an aggregated level (EU, regional or national level), we can list five main socio-economic factors.

Firstly, welfare is an important factor affecting funding allocation and expenditure. According to Lusk (2017) the adoption of agricultural subsidy programs affects aggregate welfare transferring funds to people living in the countryside or in rural communities, affecting the distribution of surplus among farmers, consumers and taxpayers. Du et al. (2017) argue that the US crop insurance subsidy program is viewed as an income transfer tool as farmers acquire subsidy transfers. As a result, agricultural producers might rely on RM subsidies for long-term investment decisions, making policy dismantling costly (Popp et al., 2021).

Secondly, the presence in the policy mix of alternative income stabilization measures, such as direct payments to producers, significantly affects the adoption and relative expenditure for the RMT. Direct farm income policies are dominant over RM policies because they provide highly visible benefits to a small group of beneficiaries (farmers) which have strong incentives for lobbying for policy continuation (Sheingate et al., 2017), and because their costs result less visible because dispersed over a large number of taxpayers (Popp et al., 2021). Evidence shows that direct payments decrease insurance demand (Chakir and Hardelin, 2010; Finger and Lehmann, 2012). The reasons are multiple: i) direct payments have an insurance effect because they reduce the variability of total farm income (Hennessy, 1998); ii) direct payments increase farmers' wealth, decreasing their risk aversion (Femenia et al., 2010); iii) direct income support reduce the beneficiaries' dependency on market income and hence on RM tools (Meraner and Finger, 2019); iv) lobbying efforts will be divided between direct income support and support for RM instead of being focused on RM tools (Popp et al., 2021).

Thirdly, the way and extent of the public intervention in RM depends on the level of development and competitiveness of the private insurance sector (Cafiero et al., 2007). On the one hand, public support for RM can disbenefit private insurance companies, leading decision-makers to decide not to put them at a disadvantage; on the other hand, in some EU MS private insurance premiums are expensive without public support, creating a financial barrier to the uptake of insurance. Therefore, decision-makers might attempt to improve the accessibility to insurance and reduce farmers' dependency on ex-post ad hoc compensation payments (European Commission, 2017).

Fourthly, past experience with support for insurance premiums influence the design and expenditure of RM policies (European Commission, 2017). In this regard, EU MS with an existing national state aid support system for subsidised agricultural insurances and mutual funds are less likely to make use of the RMT (e.g. Bulgaria, Czech Republic, Spain, for subsidized insurances; Belgium, Denmark, Belgium for mutual funds). Indeed, Rippo and Cerroni (2022) show that he adoption of the IST is influenced by previous experience with mutual funds.

Fifthly, the institutional environment also plays an important role in determining the amount of RM expenditure; for example, administrative inefficiencies (e.g. late payments by the government), the lack of experience, financial capacities, competencies and skills within the institutions, and the lack of political will or stakeholder demand. Some of the stakeholders consulted by the European Commission (2017) pointed out that the requirements in the EU Reg. 1305/2013 are too complex and difficult to implement due to insufficient clarity or explanation – particularly for aspects such as the level of excess, indemnities and financial contributions per farmer, and how to ensure liquidity and transparency to a mutual fund (European Commission, 2017). Moreover, because of organised interest/lobby groups, policymakers in one region can find it politically harmful not to subsidize areas using the RM expenditure even if they are not experiencing severe risks. On the contrary, regions with less organised agricultural interest groups may find it difficult to benefit from the RM expenditure even if they are facing higher levels of risks (Becker, 1983; Gardner, 1987). The organised interests can expect rewards from lobbying for maintaining or extending state support (Popp et al., 2021). For these reasons, Marsh and Mittelhammer (2004) pointed out that the political intentions behind policy expenditure cannot be ignored when modelling agricultural disaster relief payments. In this respect, Camaioni et al. (2016) showed that the RD expenditure is not only determined by the degree of rurality but also by the political intentions of EU regions. They argue that the expenditure observed in a given territorial level (e.g. NUTS3 level) is not only dependent on political decisions, but also on the capacity of the higher institutional level (e.g. EU, NUTS0 or NUTS1 level) to attract and use these funds. In other words, the underlying higher-level political decision (i.e. the neighbouring regions) affects the budget received and spent at the lower territorial level. Crescenzi et al. (2015) argue that political economy processes at the local level are captured by spatial interactions. Therefore, we also assume that spatial effects of the RM expenditure indicate the institutional environment surrounding the political decisions.

Concerning risks, they arise from multiple sources, such as production, market, institutional, personal, and financial risks (Komarek et al., 2020). Among these, climate change is increasing the probability of extreme weather events and the exposure to risks of European farmers. This is leading to higher demand for RM tools to hedge against multiple adverse events (Rippo and Cerroni, 2022). However, climate change is affecting the various EU MS differently. Some are suffering from a warmer environment, others from more erratic rainfall patterns or more frequent extreme events, or a combination of these risks (European Commission, 2017). Several authors (e.g. Enjolras and Sentis, 2011; Lefebvre et al., 2014; Giampietri et al., 2020) emphasized that the probability and frequency of risks explains the adoption of RM. Farmers exposed to larger local hail risks are more likely to adopt hail insurance (Finger and Lehmann, 2012). Moreover, high risk probability and high risk occurrence influence farmers' vulnerability perception leading farmers to adopt on-farm risk management solutions or to increase the participation to RM public programs (Rippo and Cerroni, 2022). Also the occurrence of unexpected events and their intensity can lead to RM adoption. Many risk managers act only in the aftermath of a major event while under expenditure on RM might be a consequence of several good growing years (Du et al., 2017). The higher the damage experienced from an extreme event, the higher the farmers' interest and willingness to pay for RM (Budhathoki et al., 2019).

Regarding agro-ecological factors, the structure of the farming system, and the location and its environmental conditions can be an obstacle for farmers to adopt RM and for the private market to develop competitiveness. This is particularly the case for highly heterogeneous and fragmented farming systems, with a prevalence of numerous small farms (European Commission, 2017). For example, Rippo and Cerroni (2022) provide evidence that in areas of the Italian region Trentino, where apple production is intensive and can form a major part of a farm's income, farmers are more willing to participate in the IST schemes with respect to the farmers in other areas with a lower apple intensity and a mixed production portfolio. Similarly, Finger and Lehmann (2012) gave evidence that in Switzerland, larger farms with specialization in crop production are more likely to adopt hail insurance. The existence of a strong relationship between land use and adoption of RM is demonstrated by the ample literature on the effects of insurance subsidies on crop acreage (see, for example, Wu, 1999; Goodwin et al., 2004; Yu et al., 2018). More variability in yields and revenues for a crop reduces the amount of land and the likelihood that the crop is planted, favouring the plantation of less risky crops (Claassen et al., 2016). This is because the expected revenues drive farmers' crops decisions. Regarding location, geography is a relevant factor when considering the types of risks faced by a farm. For example, at higher altitudes the probability of risks such as hail, low temperatures, frosts, and excessive wind, tend to increase (Mahoney et al., 2012). Indeed, the studies of Enjolras et al. (2012) and Santeramo et al. (2016) found a positive correlation between altitude and adoption of crop insurance. Moreover, a higher level of indemnification was found for upland farms in Italy (Trestini et al., 2018) and valley farms in Switzerland (El Benni et al., 2016).

4. Data and methods

The analysis is developed using NUTS3 regional data[2]. NUTS3 data have the advantage of not only providing a more detailed statistical subdivision with respect the NUTS2 or the country level, but data at NUTS3 level also allows for reducing the importance of top-down political power as driver of expenditure (Zaporozhets et al., 2016), and helping to account for the actual implementation of policies across space and the capacity of territories to attract and use funds (Camaioni et al., 2016).

Table 1 describes the variables selected, while Table 2 shows their descriptive statistics. The data source for NUTS3 regions expenditure on CAP's instruments is the CATS. These are data collected yearly by the EC of all individual payments made to the beneficiaries of CAP's Pillars I and II for audit, control and statistical purposes. While Camaioni et al. (2016) have identified three main drivers for the distribution of total RD payments (country-specific, rurality, and spatial effects), here, we are interested in comparing what motivates EU regions when considering allocating part of the total RD payments to risk management instead of other RD targets (e.g. job creation, infrastructure, …etc.). Therefore, our dependent variable is a composite variable from the sum of both M5 and M17 payments (labelled *RM expenditure*).

Table 1. Data description

Dependent variable	
RM expenditure (M17 + M05) as % of total RD	Calculated as the sum of measures 5 and 17 of the RD divided by the total RD expenditure. Data obtained from the CATS dataset.
Economic variables	
GVA per capita	Calculated as the GVA of a region divided by the region's population. Data obtained from and Eurostat [nama_10r_3gva] and [demo_r_pjangrp3].
Agricultural Value Added (% of GVA)	Calculated as the GVA of the agricultural sector divided the region's GVA. Data obtained from and Eurostat [nama_10r_3gva].
CAP subsidies (% of agriculture VA)	Calculated as total CAP expenditure divided the GVA of the agricultural sector. Data obtained from the CATS dataset and Eurostat [nama_10r_3gva].
Risk variables	
Precipitation	The Standardized Precipitation Index (SPI06), a meteorological drought indicator measuring the severity of a wet or dry event over 6-month accumulation periods. The SPI values are normalised in units of standard deviation from the long-term average of total precipitation in each location. Values lower than -1 represents day events; between -1 and 1 indicate normal precipitation; and higher than 1 represent dry events.
	(continue)

[2] Spatial polygon data for NUTS3 regions at 1:1,000,000 scale was downloaded from the Eurostat GISCO geospatial data portal.

Heatwave intensity	Calculated as the yearly average of extreme-temperature anomalies in each region multiplied by the number of hot days recorded in each year over 365. Data were constructed from the Heat and Cold Wave Index (HCWI).
Soil erosion (wind)	Average soil erosion by wind in tonnes per ha. Data obtained from JRC.
Soil erosion (water)	Average soil erosion by water in tonnes per ha. Data obtained from JRC.
Agro-ecological variables	
Land diversity index	For the land diversity index, we only consider the five rural type of land (arable, crops, pastures, heterogenous agriculture, and forest). It is calculated as 1 - Simpson's Index of Diversity (D), where $D = \sum_i^R \left(\frac{a_i}{A}\right)^2$. R is the number of land types (here are 5 types of land as below), a_i is the area of each type of land, and A is the total land area. The value of the index takes the range between 0 and 1, where the greater the value the more diversity is the land, such that 1 is completely diverse land and 0 is completely homogenous land.
Arable land (% of total area)	Calculated as total arable land (CORINE codes: 211+212+213) divided total area.
Permanent crops (% of total area)	Calculated as total permanent crops land (CORINE codes: 221+222+223) divided total area.
Pastures (% of total area)	Calculated as total pastures land (CORINE codes: 231) divided total area.
Agricultural diversity (% of total area)	Calculated as total heterogeneous agriculture land (CORINE codes: 241+242+243+244) divided total area.
Forest (% of total area)	Calculated as total land for forests (CORINE codes: 311+312+313) divided total area.
LFA (% of area)	Calculated as less favoured area divided by total area. LFA data is obtained from the European Environment Agency, and total area from CORINE land cover data.
Dummy variables	
Rural development programmes dummy variables	Dummy variables that take the values of 0 or 1 for each rural development programme.

The choice of explanatory variables is driven by the literature discussed in sections 3 and 4, therefore we hypothesize that three main factors have a role in the decisions of allocating EU funds to the RMT: socio-economic, risk and agro-ecological factors.

The socio-economic factors indicate the relative capacity of a region to cope with economic losses due to risk and disasters and also the dependence of a region's economic development on the agricultural sector. We selected three variables computed from the CATS and EUROSTAT data. These are: 1) GVA per capita: to reflect the level of economic development of the region; 2) the share of agriculture in the GVA of the region: to reflect the size and importance of the agriculture sector in a region's economy, which can inform about the influence of farmers' interest groups; and 3) total CAP subsidies as percentage of the value added of the agricultural sector: to reflect the level of alternative income stabilization financial support received by the agricultural sector in a region and to correct for differences in relative size between regions. The population data used to calculate per capita values is reported by Eurostat as of 1 January of each year, and the GVA used here is at basic prices. Because the land cover data are available only for 2018 (see below), we could not develop a panel data analysis and we transformed all the economic data in their four-year averages for the period 2015 - 2018. In this way, we obtain a cross-sectional analysis exploiting spatial variability instead of time variability.

Table 2. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
(log) RM expenditure (M17 + M05)	1,265	-0.99	1.92	-13.45	0.90
(log) GVA per capita	1,265	-3.87	0.61	-5.89	-1.98
(log) Agricultural VA	1,265	-4.19	1.55	-10.11	-1.45
(log) CAP subsidies	1,265	0.19	0.90	-6.88	3.26
Precipitation	1,265	-0.16	0.69	-2.11	1.92
(log) Heatwave Intensity	1,265	-0.18	0.73	-3.14	1.86
(log) Wind erosion	1,265	-2.57	2.72	-21.44	2.34
(log) Water erosion	1,265	0.28	1.13	-4.12	3.34
(log) Land diversity	1,265	-0.64	0.40	-4.13	-0.26
(log) Arable land	1,265	-1.75	1.33	-8.52	0.00
(log) Permanent crops	1,265	-3.11	3.02	-12.06	0.00
(log) Pastures	1,265	-2.76	1.62	-12.47	0.00
(log) Agricultural diversity	1,265	-3.29	2.00	-11.20	0.00
(log) Forest	1,265	-1.75	1.10	-9.46	0.00
(log) LFA	1,265	-0.90	1.66	-13.59	0.00

For risk factors, we used four variables to measure climate risk. For precipitation deficit and extreme heatwaves, we used the Standardized Precipitation Index (SPI) and the Heat and Cold Wave Index (HCWI) which are produced by the Copernicus European Drought Observatory (EDO). Originally developed by McKee *et al*. (1993), the SPI is used for measuring meteorological droughts by comparing observed accumulated precipitation at a specific location over a chosen period (e.g., 1, 3, 12, 48 months) with long-term historical data. The historical data are transformed into a standard normal distribution where the mean SPI is zero. The values of the SPI are then the standard deviations from the mean, where severe levels of drought are indicated by decreasing SPI below –1.0, and excess rainfall are indicated by above 1.0 SPI (Joint Research Centre, 2021a).[3] The heatwave intensity measurement identifies daily hot temperature anomalies known to significantly affect human activities as well as agricultural production. The HCWI measures heatwaves when daily minimum and maximum temperatures exceed the 90th percentile daily threshold for at least three consecutive days, using Lavaysse *et al*.'s (2018) approach and a 30-year baseline (1981-2010) (Joint Research Centre, 2021b).

[3] We did not use log-transformation with the SPI, as it is a normalized index measured as the standard deviation from the long-term mean, where the long-term has mean zero and variance of one.

Moreover, soil erosion by water and wind are major challenges for agriculture in the EU. The higher the soil erosion, the higher the probability of extreme weather events. The hypothesis is that the most high-risk regions in terms of weather exposure should be more likely to take out RM measures (Smith and Goodwin, 2013; Claassen et al., 2016). Data on soil erosion was acquired from the European Commission's Join Research Centre (JRC). Two different spatial data products were downloaded: 1) Soil erosion by water (Revised Universal Soil Loss Equation - RUSLE2015) (Panagos et al., 2015); and 2) Soil erosion by wind (Revised Wind Erosion Equation – RWEQ) (Borrelli et al., 2017). Both datasets report soil loss per raster grid square (100 x 100m for water, 1km x 1km for wind) in tonnes per hectare (T/ha). The RUSLE2015 accounts for soil erosion factors by calculating annual soil erosion by water using rainfall erosivity factor, soil erodibility factor, cover-management factor, slope length and slope steepness factor, and support practices factor (Panagos et al., 2015). Therefore, soil erosion by water is used as a proxy for rain and flood related risks. Wind erosion is caused by several factors that are included in the RWEQ using weather factor, wind-erodible fraction of soil and soil crust factor, soil roughness factor, and combined vegetation factor (Borrelli et al., 2017). Therefore, soil erosion by wind can be used as a proxy for drought-related risks.

Agro-ecological factors influence the environmental conditions under which farms operate. First, different land uses have different vulnerabilities to and resilience against environmental risk factors, and may require different levels of public support. We used land cover data from the latest CORINE data ("CLC 2018") downloaded in vector format from the European Environment Agency via the Copernicus data portal. The data comprises over two million spatial polygons showing the land cover for Europe across 44 classes, organised into five major land cover group types (Level 1 of the CLC): 1) artificial surfaces; 2) agricultural areas; 3) forests and semi-natural areas; 4) wetlands; 5) water bodies. That data has a minimum mapping unit of 25ha, and a reported thematic accuracy of > 85%. We used these data on land use also to calculate an index of land diversity as a measure for the level of heterogeneity of the farming systems. Second, location variables are important to capture unobservable effects due to local characteristics such as the profitability of agricultural production and the risk exposure (Lefebvre et al., 2014). In this respect, Less Favoured Areas (LFA) indicate upland areas or other areas where the physical landscape results in difficult and more expensive agricultural production conditions. Data on LFA location across the EU was downloaded from the European Environment Agency data portal. These areas, where agricultural production conditions are considered to be difficult, are categorised into four main classes: 1) mountain/hill areas; 2) less-favoured areas in danger of depopulation; 3) areas with specific handicaps; 4) lakes. In addition, the effect of political factors, administrative (in)efficiencies and higher institutional levels is captured by spatial dependence effects, as explained in section 4. Finally, we also include the models' specification dummy variables indicating the RDP. This is because nearby NUTS3 regions can be part of an area administered under the same RDP, therefore sharing same decision-making and expenditure patterns.

4.1. Testing spatial autocorrelation and spatial data processing

Processing, analysis, and visualisation of the spatial data was conducted using the open-source software tools QGIS (v.3.16.13), GeoDa (v.1.14.0), and R (v.3.6.1 with RStudio v.1.2.5001). For the CORINE data, land cover polygons were 'intersected' with the NUTS3 region polygons and QGIS and each assigned an ID code of the NUTS3 region in which they were located (land use polygons that straddled NUTS3 boundaries were split into smaller polygons). The total land area (km^2) of each land cover type within each NUTS3 region was then calculated by grouping and summarising the attribute table of the intersected layer using R. A similar process was used to calculate the land area of the LFA polygons within each NUTS region. For the raster soil erosion data, mean T/ha was calculated across each region using the zonal statistics tools in QGIS.

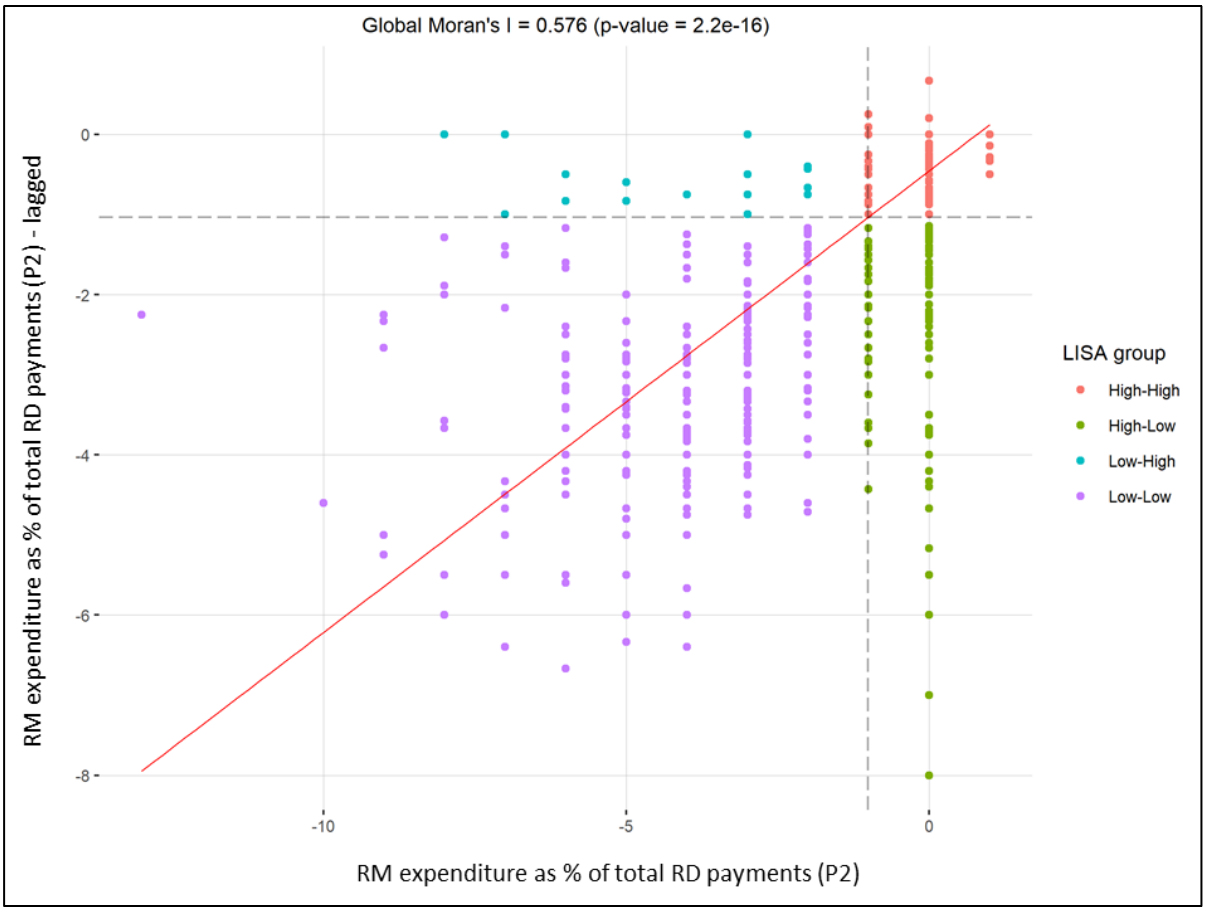
In order to assess whether a spatial regression modelling approach might be justified, a global Moran's I test (Moran, 1950) was first used to determine whether the dependent variables were spatially autocorrelated:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad (1)$$

where $\bar{x}$ is the mean of the x variable, w_{ij} are the elements of a weights matrix between regions i and j, and S_0 is the sum of the elements of the weights matrix: $S_0 = \sum_i \sum_j w_{ij}$. In this case, as in Camaioni et al.'s (2016) study, a first-order queen's contiguity matrix was adopted for the weights matrix, in favour of distance weighted or K-nearest neighbour (KNN) alternatives, due to the size heterogeneity of the NUTS3 regions. The first-order queen contiguity matrix ($\boldsymbol{W}$) is a positive and symmetric ($N \times N$) matrix that signifies for each observation i its neighboring spatial units (locations). Such that, $w_{ij} \neq 0$ if i and j are first-order neighbors, and $w_{ij} = 0$ if i and j are not first-order neighbors. The normalized spatial weights matrix is standardized by rows (observations), so that for any observation, the sum of its neighbours' weights are equals 1 (Anselin and Bera, 1998; Darmofal, 2015).

A Moran's I statistic reports a value of between -1 (strongly negatively autocorrelated – i.e. spatially heterogeneous with no spatial dependency) and +1 (strongly positively spatially autocorrelated with high spatial dependency). The resulting Moran's plot and statistic (Figure 1) indicated that the RM expenditure is positively spatially autocorrelated – the null hypothesis of spatial randomness can be rejected, providing justification for further analysis using spatial regression modelling.

Figure 1. Moran's I plot for RMT expenditure

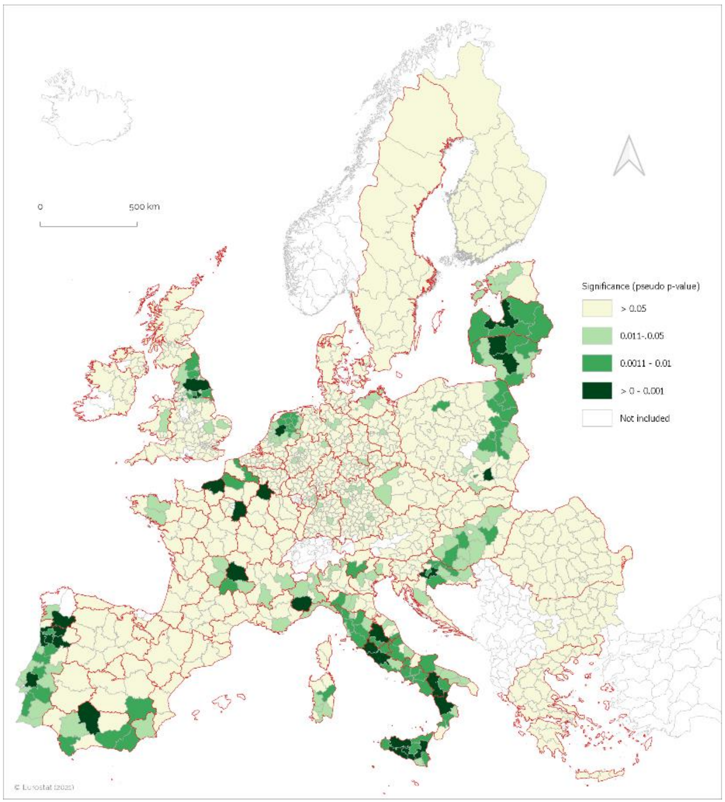


The global Moran's I statistic provides useful evidence for rejecting the null hypothesis of complete spatial randomness but does not tell us which where any significant clusters or outliers are located. To visualise spatial clusters and obtain a local measure of spatial autocorrelation, we computed a local indicator of spatial association (LISA) statistic for the dependent variable (Anselin, 1995): $I_i = c.z_i \sum_j w_{ij} z_j$

With LISA, a local Moran statistic is computed for each observation (NUTS3 region) i by comparing its value to the spatially lagged mean of its neighbours. Importantly, the significance of the statistic for each location is reported as pseudo *p*-value, calculated using a conditional permutation approach (using *n* number of randomised permutations to compare the results to a reference distribution). The results of LISA performed on the dependent variables with the default GeoDa settings of 999 permutations (normally sufficient for reliable inference) and a *p*-value of 0.05 are shown in the significance maps (Figure 2) and cluster map (Figure 3). In Figure 2, the significance of local statistic is reflected in increasingly darker shades of green. In Figure 3, the map provides an indication of the type of spatial association for significant observations, based on their values in relation to neighbouring regions.

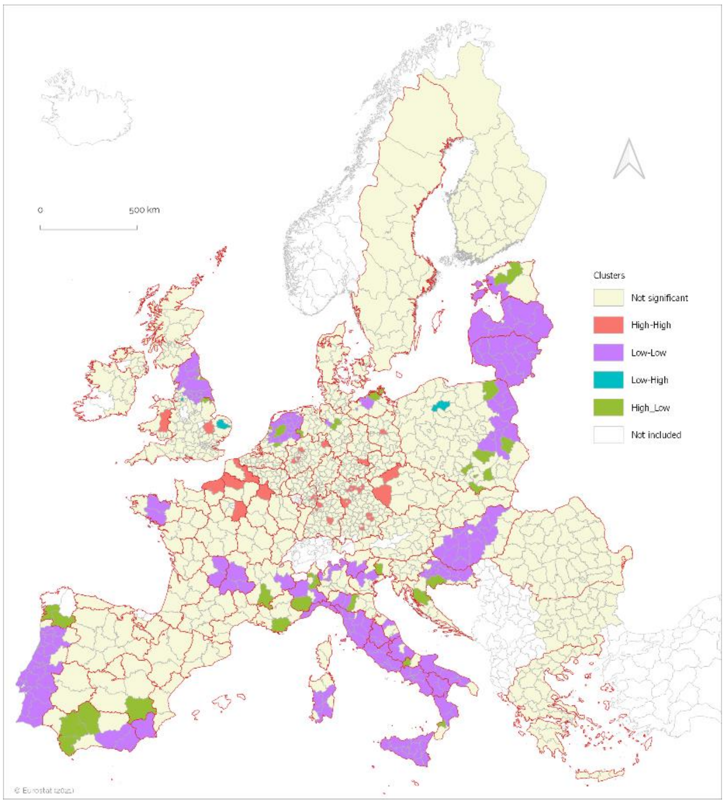
A critical issue in estimating spatial dependence in RMT expenditure patterns is verifying whether it is driven by RDPs. That is, RDPs can be national or regional and one RDP can manage multiple NUTS3 regions. In Figures 2 and 3 we report both the RDPs administrative regions (in red) and the NUTS3 regions (in grey). For example, Poland has a single national RDP; Italy has one national RDP (which administers M5 and M17) and 21 regional RDPs. As one can see, significance (Figure 2) and clusters (Figure 3) do not follow the RDPs borders, indicating that RMT expenditure significantly differs across NUTS3 regions within the same RDP. In other words, RDPs do not fully explain expenditure, but there are further factors driving the use of RMT.

Figure 2. Local indicators of spatial autocorrelation (LISA) significance map for RMT over Pillar 2 payments



Notes: red borders indicate RDPs administrative regions; grey borders indicate NUTS3 regions.

Figure 3. Local indicators of spatial autocorrelation (LISA) cluster map for RMT over Pillar 2 payments



Notes: red borders indicate RDPs administrative regions; grey borders indicate NUTS3 regions.

4.2. Spatial autoregressive models

The results of the Moran's I test in the previous section rejects the assumption that the error is i.i.d. and suggest the presence of spatial dependence among the risk management expenditures (see also Table 3). Therefore, a spatial econometric approach accounting for spatial autocorrelation of the data, is preferred. Anselin and Bera (1998: 241) define spatial autocorrelation as *"the coincidence of value similarity with locational similarity. In other words, high or low values for a random variable tend to cluster in space (positive spatial autocorrelation), or locations tend to be surrounded by neighbours with very dissimilar values (negative spatial autocorrelation)".* According to Manski (1993) and as illustrated by Camaioni et al. (2016), there are three different types of spatial interactions which can cause spatial effects or spatial autocorrelation, which are:

1) An endogenous effect (ρ), where the observed dependent variable $\boldsymbol{y_i}$ in one spatial unit correlates with the dependent variable of other neighbouring spatial units $\boldsymbol{y_j}$;
2) An exogenous effect (θ), where the observed dependent variable $\boldsymbol{y_i}$ in one spatial unit correlates with the explanatory variables of other neighbouring spatial units $\boldsymbol{X_j}$; and

3) A correlated effect (λ), where observations of the $\boldsymbol{i}$ and $\boldsymbol{j}$ spatial units are correlated due to unobserved characteristics that are represented by the disturbance term, $\boldsymbol{\varepsilon}$.

The general model proposed by Manski (1993) is the general nesting spatial (GNS) model which accounts for the three spatial effects. The GNS model is theoretically plausible but cannot be empirically estimated because not all parameters can be identified simultaneously, and ρ and θ are not fully distinguished from one another (Manski, 1993; Elhorst, 2010; Camaioni et al., 2016). The solution to this problem is to assume that one or two of the spatial parameters ρ, θ, or λ is equal to zero and different models have adopt such strategies. The spatial error model (SEM) assumes that $\rho = \theta = 0$, and estimates the spatial effect λ within the error terms. The spatial lag of X variables (SLX) model assumes that $\rho = \lambda = 0$ and estimates the spatial effect θ of the neighbouring variables. The spatial autoregressive (SAR) model assumes $\theta = \lambda = 0$ and that different values of the dependent variable $\boldsymbol{Y}$ depend on the neighbouring dependent values of $\boldsymbol{Y}$. The spatial autoregressive combined (SAC) model assumes that only $\theta = 0$ and estimates the spatial effects ρ and λ of the dependent variable and the error term[4].

In addition, the spatial Durbin model (SDM) and the spatial Durbin error model (SDEM) are also frequently used in the literature. The SDM assumes $\lambda = 0$ and allows for the estimation of ρ and θ simultaneously:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{WY} + \beta_x \boldsymbol{X} + \theta \boldsymbol{WX} + \boldsymbol{\varepsilon} \qquad (2).$$

Where $\boldsymbol{Y} = y_i, (i = 1, \dots, N)$ is the dependent variable (RMT expenditure) in the form of $(N \times 1)$ vector, and N is the number of NUTS3 regions considered ($N = 1{,}265$). β_0 is the intercept (constant) term**.** $\boldsymbol{X}$ is an $(N \times K)$ matrix of variables representing: 1) Socio-economic factors (GVA per capita; Agricultural value added; CAP subsidies); 2) Risk factors (wind and water soil erosion); 3) Agro-environmental factors (land diversity index; type of land cover among arable, permanent crops, pastures, agricultural diversity, and forests; LFA); 4) RDP dummy variables. Variables are log transformed, and CAP expenditures, agricultural value added and GVA per capita are four-years averages. $\boldsymbol{W}$ is the $(N \times N)$ normalized spatial weight matrix. $\boldsymbol{WY}$ and $\boldsymbol{WX}$ are $(N \times 1)$ vectors representing the spatial lags for the dependent variable $\boldsymbol{Y}$ and independent variables $\boldsymbol{X}$, and ρ and θ are scalar parameters for the spatial effects that need to be estimated for the dependent variable and independent variables, respectively. Finally, $\boldsymbol{\varepsilon}$ is the disturbance or error term that is assumed to be

[4] All the equations are outlined in more detail in Appendix 1.

independent and identically distributed (i.i.d) with an expected value of zero and a constant variance, that is $\varepsilon_n \sim (0, \sigma^2)$.

The SDM estimates the global effects of independent variables or the total impacts of changes in $\boldsymbol{X}$, which are complex to interpret. In the SDM, the influence of the first-order variables is not only expressed by θ, but it is also reflected in the influence of the variables of the neighbouring spatial unit, that is $\beta_j \boldsymbol{X_j}$ on $\boldsymbol{Y_j}$, which is transferred to the i spatial unit through $\rho \boldsymbol{WY}$. This is referred to as the global multiplier because the spillover effect of the spatially lagged dependent variable is determined by both the dependent variable itself as well as the spatial lagged variables. With the global effects, we cannot distinguish between the effect of the bordering region (first-order effects) and the effect of all other non-bordering regions in the sample, because a change in the variable of any region can potentially influence the dependent variable of all other regions (LeSage and Pace, 2009).

The SDEM assumes only $\rho = 0$ and estimates the spatial effects of the variables and the error term:

$$\begin{gathered} \boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \theta \boldsymbol{WX} + \mathbf{u} \\ \mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \end{gathered} \tag{3}$$

Where $\boldsymbol{W}\mathbf{u}$ is a $(N \times 1)$ vector representing the spatial matrix for the error term $\mathbf{u}$, and λ is a scalar parameter for the error term spatial effects that needs to be estimated. Although the SDEM does not include a separate effect for the spatial lagged dependent variable $\boldsymbol{Y}$, it estimates the direct effects of the variables $\boldsymbol{X}$ (represented by the coefficients β) whereas the indirect effect of the neighbouring regions is represented by θ. The SDEM shows the local multipliers, or the effects of the close neighbouring spatial units (or first-order effects), instead of the global multiplier. Thus, the SDEM is more efficient for modelling first-order spatial effects, although it can underestimate higher-order (global) indirect effects (LeSage and Pace, 2009). Because not all the EU MS or regions have allocated funds for the RMT, and given that the LISA showed clear spatial autoregressive clustering across nearby regions, the spatial effects of the factors affecting risk management expenditures are essentially generated by local neighbour regions influences rather than by higher-order spatial effects produced by distant no-bordering regions.

All the models described above can be estimated with Maximum Likelihood (ML), instrumental variables or generalized method of moments (IV/GMM), or Bayesian estimators. Our main results are obtained using the ML estimator using quasi–maximum likelihood. ML estimator is more commonly used in the literature (e.g. Camaioni et al., 2016) because it can produce consistent and efficient estimates while relaxing the normality assumption (LeSage and Pace, 2004). In addition, the Akaike Information Criterion (AIC) and the likelihood ratio (LR) test can only be used with ML estimator, which are helpful to measure the goodness-of-fit of the estimates and to choose between the different model specifications as described earlier. We use robust standard errors to control for non-normal and identically distributed i.i.d errors. Moreover, to relax the assumption that the error term is i.i.d, $\boldsymbol{\varepsilon_n} \sim (\boldsymbol{0}, \boldsymbol{\sigma^2 I})$, we also estimated our models using the GS2SLS IV/GMM estimator after controlling for heteroskedasticity. The GS2SLS estimates are reported in the annexes (Appendix 3) for comparison purposes. Overall, the GS2SLS estimations are similar to the ML estimations reported in table 3.

5. Results

Table 3 reports the estimates for the determinants of the total RMT expenditure (M5 plus M17). In order to evaluate the consistency of the estimations, we performed the testing procedure proposed by Elhorst (2010). Firstly, we tested for the presence of spatial dependence using the Moran's I test on an OLS estimation of our specification (table 3, column 1). The Moran's I test rejects the null hypothesis that the estimated residuals are spatially independent, confirming that spatial autoregressive models are more appropriate (LeSage and Pace, 2009). The AIC also indicates that the spatial autoregressive models fit the data better than the OLS estimation. Second, we calculated the differences between the estimated total residuals and the uncorrelated residuals (uncorrelated error term) to examine if the estimate residuals are correlated (*Std. dev. in res. diff.*). The predicted estimates suggest that the total residuals are not different from the uncorrelated residuals in the SAR, SLX, and SDM estimates as the difference between the residuals have a zero mean and zero standard deviation. Third, we used the Likelihood-ratio (LR) test to examine if the constrained models (SEM, SAR, SLX, SDM, SDEM, and SAC) were a good fit for our data compared with the unconstrained model (the GNS). The LR test rejects the null hypothesis that the constrained models fit the data better than the unconstrained model, except for the SDM estimates (column 5), suggesting that the SDM specification has the best fit for our data. Finally, we test for the validity of the SDM using the LR test, to examine whether: i) the SDM can be simplified to the SLX ($\theta = 0$); ii) the SDM can be simplified to the SEM ($\theta + \rho\,\beta = 0$). Given that we cannot reject these hypotheses – i.e. in the absence of empirical evidence that supports a specific spatial model, Elhorst (2010) suggests to test whether the SDM can be simplified to either the SLX or the SDEM ($\rho = 0$). The result rejects this last test, further confirming that the SDM specification is best suited to the data analysed.

In table 3, the coefficients β represent the effects of the variables $\mathbf{X}$ of the i region on its own dependent variable y_i. In other words, they represent the direct effects of the various determinants on a region's RMT expenditure. The spatial effects are expressed through the parameters λ, ρ and θ. Columns (2),

(3) and (4) estimate each spatial effect at a time, while columns (5), (6), and (7) estimate different combinations of spatial effects. The spatial effects of both the lagged RMT expenditure (ρ) and lagged variables (θ) is estimated by SDM in column (5); spatially dependent errors (λ) and spatial lagged variables effects (θ) are estimated by SDEM in column (6); finally, column (7) reports the estimates for the SAC that combines the spatially dependent errors (λ) with the spatial lagged RMT expenditure (ρ). Results are consistent across the models in the different columns, suggesting a robust empirical specification and variables choice.

λ is a spatial error term which indicates the unknown or unmeasurable spatial dependence that affects the RMT expenditure. It is statistically significant at 1% level in each column (2), (6) and (7), indicating the presence of geographical clustering (Darmofal, 2015). This effect is in line with Crescenzi et al. (2015) which found significant and positive λ parameters for RD policies in the period 1994-2013, although they found also insignificant λ parameters for Pillar I CAP policies.

ρ indicates the spatial spill overs of the RMT expenditure of the j region on its neighbouring region i. There is a 1% statistically significant spatial lag dependent variable ρ in columns (3) and (5), suggesting that RMT expenditure in one region is positively dependent on the neighbouring regions' RMT expenditure. A similar effect was found by Crescenzi et al. (2015) for RD policies in 2007-2013, although they found no effect for the previous programming period 2000-2006 and a small negative effect for the programming period 1994-1999. The significance of spatial spillovers of the RMT expenditure between regions suggests spatial interactions due to political economy processes that were not captured by the socio-economic, risk and agro-ecological explanatory variables, reflecting the influence of the higher institutional environment at the local level (De Filippis et al., 2013).

θ is the spatial effect due to the spatial lagged variables (indirect effect), meaning that the dependent variable y of region i is not only explained by the variables $\mathbf{X}$, but also by the variables $\mathbf{WX}$ of its neighbouring regions j. These indirect effects are estimated in columns (4), (5) and (6).

The spatial effects ρ and θ of the SDM represent global effects, meaning that they include spill overs from the neighbouring regions as well as the influence of higher-degree indirect impacts from other regions (Elhorst, 2010). Camaioni et al. (2016) explained that the global effects should not be ignored when analysing RD expenditure, as the expenditure in one region can be influenced by the overall budget constraint of the EU or the MS that has an influence beyond the first-degree neighbouring regions. On the contrary, the SDEM captures the local spatial effects which are mainly driven by local clustering.

Table 3. ML estimations for factors influencing Risk Management expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	SEM	SAR	SLX	SDM	SDEM	SAC
β(**X**):							
GVA per capita	-0.015	-0.131	-0.001	-0.013	-0.068	-0.030	-0.153
	(0.18)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)
Agricultural VA	**-0.109****	**-0.104****	**-0.073***	-0.070	-0.077	-0.079	**-0.110****
	(0.044)	**(0.044)**	**(0.041)**	(0.050)	(0.049)	(0.048)	**(0.045)**
CAP subsidies	**-0.215*****	**-0.175*****	**-0.162*****	**-0.202*****	**-0.191*****	**-0.207*****	**-0.181*****
	(0.059)	**(0.057)**	**(0.055)**	**(0.061)**	**(0.060)**	**(0.059)**	**(0.058)**
Precipitation	0.070	0.086	0.077	0.082	0.092	0.091	0.087
	(0.063)	(0.057)	(0.059)	(0.061)	(0.059)	(0.061)	(0.056)
Heatwave intensity	0.041	0.019	0.028	0.030	0.038	0.049	0.016
	(0.064)	(0.063)	(0.059)	(0.067)	(0.066)	(0.064)	(0.063)
Wind erosion	0.006	0.008	0.004	0.009	0.010	0.011	0.009
	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)
Water erosion	-0.107	-0.052	-0.103	0.101	0.088	0.067	-0.040
	(0.068)	(0.072)	(0.063)	(0.088)	(0.086)	(0.084)	(0.074)
Land diversity	0.124	0.074	0.114	0.068	0.061	0.071	0.065
	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
Arable land	**0.092****	**0.097****	**0.094****	0.060	0.063	0.059	**0.096****
	(0.044)	**(0.043)**	**(0.041)**	(0.046)	(0.044)	(0.044)	**(0.043)**
Permanent crops	-0.016	-0.003	-0.012	-0.016	-0.011	-0.016	-0.001
	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)
Pastures	0.001	0.002	0.002	0.021	0.015	0.012	0.003
	(0.038)	(0.036)	(0.035)	(0.038)	(0.037)	(0.036)	(0.036)
Agricultural diversity	0.026	0.034	0.028	0.022	0.028	0.025	0.035
	(0.026)	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)
Forest	0.012	0.018	0.024	0.046	0.052	0.054	0.016
	(0.053)	(0.051)	(0.049)	(0.053)	(0.052)	(0.051)	(0.051)
LFA	0.026	0.026	0.030	0.026	0.026	0.026	0.026
	(0.025)	(0.023)	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)
Constant	-0.069						
	(1.46)						
RDP regions dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W							
λ(**Wu**)		**0.476*****				**0.354*****	**0.547*****
		(0.045)				**(0.049)**	**(0.069)**
ρ(**WY**)			**0.315*****		**0.349*****		-0.079
			(0.042)		**(0.048)**		(0.077)
θ(**WX**):							
GVA per capita				**1.133****	**0.904***	0.816	
				(0.48)	**(0.47)**	(0.52)	
Agricultural VA				-0.137	-0.061	-0.092	
				(0.12)	(0.12)	(0.13)	
CAP subsidies				**-0.583*****	**-0.433****	**-0.558*****	
				(0.18)	**(0.17)**	**(0.19)**	
Precipitation				-0.200	-0.128	-0.038	
				(0.19)	(0.18)	(0.20)	
Heatwave intensity				0.139	0.064	0.035	
				(0.16)	(0.15)	(0.17)	
Wind erosion				-0.038	-0.019	0.002	
				(0.049)	(0.048)	(0.052)	
Water erosion				**-0.328***	-0.211	-0.195	
				(0.17)	(0.17)	(0.19)	
Land diversity				0.218	0.169	0.352	
				(0.39)	(0.38)	(0.42)	
Arable land				0.046	-0.011	-0.016	
				(0.13)	(0.13)	(0.14)	
Permanent crops				**-0.120*****	**-0.098*****	**-0.117*****	
				(0.038)	**(0.037)**	**(0.041)**	

(continue)

Pastures				0.029	0.047	0.062	
				(0.11)	(0.10)	(0.11)	
Agricultural diversity				-0.124	**-0.126***	-0.127	
				(0.076)	**(0.074)**	(0.081)	
Forest				-0.046	-0.072	-0.098	
				(0.15)	(0.15)	(0.17)	
LFA				0.050	0.033	0.038	
				(0.067)	(0.065)	(0.072)	
RDP regions dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1265	1265	1265	1265	1265	1265	1265
R^2 / Pseudo R^2	0.596						
F / Wald chi^2	**15.04*****	**1477.1*****	**2953.0*****	**3323.7*****	**3539.3*****	**2131.6*****	**1339.8*****
Moran (*p*-value)	**0.000**						
LR chi^2 (nested in GNS)		152.8***	172.07***	47.9***	**1.38**	9.29***	152.16***
Std. dev. in res. diff.		0.257	**0.000**	**0.000**	**0.000**	0.158	0.315
$\lambda(\mathbf{Wu}) = 0$		**0.000**				**0.000**	**0.000**
$\rho(\mathbf{WY}) = 0$			**0.000**		**0.000**		0.305
$\theta(\mathbf{WX}) = 0$				0.108	0.118	0.269	
$\theta + \rho\,\beta = 0$					0.186		
$\lambda + \rho = 0$							**0.000**
$\lambda + \theta = 0$						0.269	
$\rho + \theta = 0$					0.118		
AIC		4245.0	4264.3	4356.0	4312.9	4321.4	4246.4
BIC	4902.6	4841.6	4860.9	5513.2	5475.2	5483.7	4848.1

OLS = Ordinary Least Squares; SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDM = spatial Durbin model; SDEM = spatial Durbin error model; SAC = spatial autoregressive combined model.
Robust standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < 0.01$.

However, the coefficients of agricultural VA and arable land in columns (1), (2), and (3) are insignificant when controlling for the spatial effects in columns (4), (5), and (6), suggesting a predominance of indirect effects over direct effects. A negative and 5%-10% statistically significant β of agricultural VA in columns (1), (2), (3) and (7) contrast with other authors' findings. Jensen et al. (2018) indicated that the ratio of agricultural VA approximates the relative income risk associated with agricultural risks. Higher levels of agricultural VA indicate a region has a higher economic dependence on the agricultural sector, and therefore it is likely that stakeholders' demand (and policymakers adopt) strategies that reduce risks of agricultural VA losses (Giampietri et al., 2020; Popp et al., 2021). On the contrary, the small positive and 5% statistically significant β coefficient of arable land in columns (1), (2), (3) and (7) is in line with previous studies. Lusk (2017) showed that in the US in 2013 the largest share of insurance subsidies was given to annual arable crops, with most subsidized premiums given to corn. Subsidies on annual crops represented 6% of the value of production, against 1% on permanent crops (Lusk, 2017).

Among the socio-economic factors, CAP subsidies remain negative and statistically significant across all models and coefficients β and θ. This suggests a compensation effect between the relative amount of total CAP subsidies received by a region and its neighbours and the allocation of RMT expenditure in that region. In other words, regions receiving high amounts of CAP subsidies are less likely to allocate funds for the RMT. As pointed out by Popp et al. (2021), in most OECD countries RM subsidies play a minor role within overall agricultural policy portfolios, and income support instruments such as area-based direct payments or market interventions often dominate. The beneficiaries of income support policies are less dependent on their market income, reducing farmers' demand for RM tools (Meraner and Finger, 2019). This might occur because direct payments are non-volatile income sources which reduce the variability of total farm income - i.e., they have an insurance effect. Moreover, direct payments might increase farmers' wealth which is expected to reduce their level of risk aversion (wealth effect), hence reducing farmers' demand for RM (Hennessy, 1998; Femenia et al., 2010). Evidence of this is provided by Finger and Lehmann (2012), who demonstrated that the introduction of direct payments in Switzerland contributed to decreasing hail insurance adoption rates. Similarly, Chakir and Hardelin (2010) has shown that direct subsidies negatively affected insurance demand in rapeseed production in the Department of Meuse (France). Our results are in line with these studies: the CAP provides overall income support to farms in regions that receive large amounts of support relative to the size of the agricultural sector, enabling the farming system to mitigate risks without the need for additional support from the RMT. Indeed, income support from the CAP's payments can help farms directly during crises (Berry et al., 2022), as well as indirectly through accumulating capital during periods of stability which make them financially prepared during periods of crisis (Khafagy and Vigani, 2022 and 2023). Note that the negative coefficients of CAP subsidies also indicate that regions that receive lower amounts of CAP subsidies are more likely to spend more on the RMT. This is in line with Popp et al. (2021) which points out that the absence of income support instruments is likely to be an important factor for the development of RM policy instruments.

Regarding agro-ecological factors, permanent crops have a negative and statistically significant θ in all three models SLX, SDM and SDEM, suggesting that increasing percentages of permanent crops area in neighbouring regions are negatively associated to RMT expenditure in the underlying region. This result might seem counterintuitive, but the literature supports the fact that often most RM subsidies are given to annual rather than perennial crops. Lusk (2017) reports that in the US in 2013 93% of insurance subsidies were given to annual arable crops (cereals, vegetables and oilseeds) with only 4% allocated to permanent crops (fruits and tree nuts). Lefebvre et al. (2014) show that farms growing permanent crops are less likely to get insured with respect mixed farms. Therefore, the negative sign of the coefficient θ of permanent crops might indicate a substitution between the RMT and alternative RM policies and tools. Firstly, the CAP's Pillar I provides additional crisis support to the fruit, vegetables and wine sectors through the CMO, by promoting producers' organizations, mutual funds, and harvest insurance. Secondly, many EU MS adopted ex-ante and ex-post national aid measures for the fruit, vegetables and wine sectors (Bardají et al., 2016). Moreover, technical tools and on-farm practices might also play a substitution role. Irrigation is usually related to high-value crops such as fruit trees and vineyards (Lefebvre et al., 2014) and it can serve as a form of self-insurance as it reduces the variance of profits (Foudi and Erdlenbruch, 2012). Preventative measures such as anti-hail nets and anti-frost systems are quite diffuse among growers of permanent crops (Rippo and Cerroni, 2022). Alternative coping tools such as farm diversification (Enjolras and Sentis, 2011) and off-farm income (Vigani and Kathage, 2019) can also play a role[5]. While with the data at hand we are unable to capture differences in the adoption of the RMT between permanent crop types, it is likely that permanent crop specialization also plays a role in explaining RMT budget allocation. Indeed, Rippo and Cerroni (2022) explain that the adoption of the IST is influenced by crop production specialisation. Among permanent crops, the olive oil sector receives one of the largest aids from the EU's CAP (Antón and Kimura, 2011), influencing risk perception and behaviour of olive farmers, as well as the adoption of the RMT in regions such as Attiki in Greece, Andalucía in Spain and Calabria in Italy that have more than 30% of UAA cultivated with olives. In wine farms, risk management involves long-term decision making from the vine planting and growing, through wine processing and aging, until wine marketing and selling (Seccia, et al., 2016; De Salvo et al., 2019) and wine farms are particularly sensitive to managerial risks (De Salvo et al, 2019) which are of non-hazard nature (e.g. change in wine demand, competitor strategies). These factors might influence the adoption of the RMT in the EU regions with higher share of grape area over total UAA, such as Languedoc-Roussillon in France and La Rioja in Spain.

Higher GVA per capita of neighbouring regions has a positive and statistically significant coefficient θ in SLX and SDM. GVA per capita is one of the socio-economic factors and measures regional economic development and wealth. In the literature, evidence of wealth effects on the demand for RM offers contradictory evidence, finding either positive effects (e.g. Cole et al., 2013) or negative effects (e.g. McIntosh et al., 2013). Economic development is associated with higher levels of education and access to information, and our result is in line with studies on their association with RM adoption. Giampietri et al. (2020) explains that better educated farmers are likely to use insurance products because they can assess risks more precisely (El Benni et al., 2016). Higher access to information also allows to assess risks more precisely and therefore play a role in determining risk exposure and the need for RM (Lefebvre et al., 2014).

Water erosion is the only risk factor showing some statistical significance. It has a negative and 5% statistically significant indirect effect θ, implying that a higher probability of rain and flood related risks in neighbouring regions are associated with less RMT expenditure in the underlying region. However, this effect concerns only θ for the SLX in column (4). The fact that we do not find a significant effect of water erosion in β weakens this result. Moreover, the effect of water erosion is not supported by the

[5] In addition to A*gricultural diversity*, we have tested a variable on *Other output* which measures the amount of output of farms holdings coming from non-agricultural activities, as a proxy for income diversification. The variable is not significant and it has a large number of missing regions. Results are displayed in Appendix 4.

SDM and SDEM which by combining θ with ρ and λ, respectively, better approximate the (theoretical) GNS model, hence providing more robust results. Other climate risk indicators were also statistically insignificant in all our models, namely soil erosion by wind, risk of precipitation deficit, and intensity of heatwaves. Therefore, we conclude that, overall, we did not find that the effect of risks was driving RMT expenditure.

In order to better disentangle the role of local and global effects, table 4 reports the estimates of the direct, indirect, and total average marginal effects of the factors on the reduced-form mean of the RMT expenditure (dependent variable) for the SDM and SDEM estimates. The results in table 4 are in line with previous results of the parameters β and θ in table 3, suggesting once again that the analysis' approach is robust. Moreover, from table 4 we observe that socio-economic factors are the most important factors affecting of RMT expenditure and that permanent crops are the most relevant agro-ecological factor, while we did not find that the effect of risks was significant. Columns (3) and (6) of table 4 confirm statistically significant net negative effects of CAP subsidies and permanent crops. Column (1) indicates that a high agricultural VA has a negative and significant direct impact, while columns (2) and (3) indicate positive, indirect and total significant effects of GVA per capita.

Table 4. Mean direct, indirect and total effect estimates

	(1)	(2)	(3)	(4)	(5)	(6)
		SDM			SDEM	
	Direct	Indirect	Total	Direct	Indirect	Total
GVA per capita	-0.025	**0.955***	**0.930***	-0.030	0.631	0.601
	(0.170)	**(0.504)**	**(0.544)**	(0.170)	(0.403)	(0.442)
Agricultural VA	**-0.081***	-0.095	-0.175	-0.079	-0.071	-0.150
	(0.047)	(0.124)	(0.123)	(0.048)	(0.102)	(0.101)
CAP subsidies	**-0.216*****	**-0.542*****	**-0.758*****	**-0.207*****	**-0.431*****	**-0.639*****
	(0.059)	**(0.182)**	**(0.189)**	**(0.059)**	**(0.145)**	**(0.151)**
Precipitation	0.087	-0.105	-0.018	0.091	-0.029	0.062
	(0.062)	(0.201)	(0.232)	(0.061)	(0.153)	(0.184)
Heatwave intensity	0.042	0.084	0.126	0.048	0.027	0.075
	(0.064)	(0.159)	(0.162)	(0.064)	(0.133)	(0.136)
Wind erosion	0.009	-0.017	-0.008	0.011	0.002	0.012
	(0.017)	(0.052)	(0.057)	(0.017)	(0.040)	(0.045)
Water erosion	0.079	-0.195	-0.116	0.067	-0.151	-0.083
	(0.083)	(0.165)	(0.152)	(0.084)	(0.144)	(0.130)
Land diversity	0.070	0.206	0.276	0.071	0.272	0.343
	(0.124)	(0.401)	(0.411)	(0.125)	(0.322)	(0.328)
Arable land	0.064	0.012	0.076	0.059	-0.012	0.047
	(0.043)	(0.133)	(0.136)	(0.044)	(0.106)	(0.108)
Permanent crops	-0.016	**-0.111*****	**-0.126*****	-0.016	**-0.091*****	**-0.106*****
	(0.013)	**(0.040)**	**(0.045)**	(0.013)	**(0.032)**	**(0.036)**
Pastures	0.017	0.056	0.074	0.012	0.048	0.059
	(0.036)	(0.110)	(0.116)	(0.036)	(0.087)	(0.092)

(continue)

Agricultural diversity	0.023	-0.126	-0.103	0.025	-0.098	-0.073
	(0.024)	(0.081)	(0.089)	(0.024)	(0.062)	(0.070)
Forest	0.050	-0.058	-0.009	0.054	-0.076	-0.022
	(0.051)	(0.158)	(0.164)	(0.051)	(0.128)	(0.133)
LFA	0.028	0.046	0.073	0.026	0.029	0.055
	(0.024)	(0.071)	(0.079)	(0.024)	(0.056)	(0.064)

SDM = spatial Durbin model; SDEM = spatial Durbin error model. Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < 0.01$. The total effect is the sum of the direct and indirect effects.

6. Conclusions

This paper analysed the spatial, socio-economic, risk, and agro-ecological factors potentially affecting the public expenditure on the RMT funded by the EAFRD. The results indicate a predominant role of socio-economic factors over risk and agro-ecological factors. Higher expenditure towards RMT occurs in more affluent regions with a higher gross VA per capita. This effect is reinforced by the presence of neighbouring affluent regions, suggesting that RMT expenditure is higher in areas with clusters of relatively high welfare. On the contrary, higher CAP subsidies tend to reduce expenditure towards the RMT, indicating a trade-off between expenditure for RM and expenditure for other rural development and direct payments. Direct subsidies with their income stabilization capacity might be used in alternative to RM. However, as pointed out by the European Commission (2017), direct payments are not designed to manage variations of income. Therefore, direct payments might not contribute to reducing risks, especially for those farms facing the largest variations in income, as they are given regardless production or market risks occur. The results also show a strong spatial dependence between NUTS3 regions on the level of RMT expenditure, which indicates the importance of the higher-level institutional environment (e.g. RD program, national government, the EU) in the local expenditure for RMT as well as political economy processes such as the activities of organized interests groups and the decisions taken at the political level. Interestingly, our results show that regions with high agricultural VA and a greater presence of permanent crops are less likely to spend much of their CAP budget on the RMT. This can be due to the fact that farmers engaging in agricultural systems with high VA, especially permanent crops, have a greater interest in protecting their production and fix crop investments through private RM products, such as multi-peril crop insurances, which compensate damages more rapidly and independently. For example, permanent crops are highly vulnerable to hail damage and private insurance is frequently sought to mitigate this phenomenon. A higher adoption of private insurance can reduce the demand for public RM tools and farmers' lobbying efforts might be directed towards other policies. Moreover, institutional constraints can also play a role in reducing the demand for RMT by these types of agricultural systems, such as a lack of experience in mutual funds or a lower historical collaboration with local governments and between farmers.

The results of this paper are relevant in the context of the current CAP's programming period. In the new CAP reform 2023 – 2027 the support to agricultural RM has been confirmed and relaunched by policies which reinforce and enlarge those implemented in the CAP period 2014-2020 such as the RMT. An important novelty are the CAP Strategic Plans to implement the new CAP at the national level, taking into account local conditions while being consistent with the EU legislation and objectives. The plans serve to improve the flexibility in applying the CAP at the national level and to adapt the support across the different EU farming systems. Greater flexibility is given also by allowing EU MS to transfer a maximum of 25% of the budget between income support and rural development. Despite the new flexibility provided by the CAP Strategic Plans, once again the support for risk management has not been as popular as expected. Direct payments remain the dominant type of economic support across the plans (Münch et al., 2023) and only fourteen EU MS included in their CAP Strategic Plans RM tools, and all of them have (to some extent) adopted the RMT in the past, confirming that past experience is important for the adoption of RM tools. Only three EU MS have transferred funds from direct payments to RM, confirming the substitution between these two support tools.

Our results inform about the past CAP programming period but draw insights also for the application of the current programming period. First of all, the adoption of RM policies follows a geographical pattern. In other words, these policies are not adopted by EU regions in isolation, but they are driven by mutual influences of the nearby regions. This also explains the relatively low rate of adoption of the RMT. Given that the RMT was adopted by contiguous regions grouped in clusters, its adoption is linked to spill over effects, probably as a result of sharing positive experiences with the policy and sharing similar agro-ecological conditions. Not having examples of neighbouring regions adopting such policies might have worked as a disincentive factor or, on the contrary, nearby examples might have demonstrated the utility of such policies. Examples and case studies illustrating the functionalities of RM policies might incentivize their adoption also in regions far away from these clusters.

Secondly, there are certain land cover types that drive the adoption of the RMT. This suggests that, on the one hand, there are a few agricultural sectors that are in more need of RM policies than others; on the other hand, it might also suggest that the RMT was designed in such a way that was not effective or attractive for many other agricultural sectors, excluding them *de facto*. Given the highly diversified nature of EU agriculture, the design of RM policies should consider a wider and more flexible range of sectorial needs and specificities also within a country.

Thirdly, agriculture intensive regions spend less public money on RM policies. This might be since in these regions the agricultural sector receives more support from direct CAP payments and other RD measures. These other forms of support also induce farm income stability and generate sufficient liquidity to deal with unexpected damages. Therefore, EAFRD funds are spent on other RD measures than the RMT. On the contrary, LFA are more likely to need RMT support against damage caused by shocks.

In order to improve the uptake of RM policies by local administrations, a few steps could be taken. Unless the mutual funds and IST build up significant reserves, they will need reinsurance services or similar tools to transfer the risks associated to compensations resulting from severe market or sanitary crisis. It is thus desirable that instruments have the broadest base and attract diverse farmers from different regions. This complicates the management of the instruments, but significantly reduces reinsurance needs. The flexibility provided by the past and current CAP reforms allows MS to rely on their own systems and instruments, helping MS improve them and broaden them, and never put at risk the systems that work and have provided valuable services to the farmers. Because they offer protection against income losses, both IST and income insurance represent a significant departure from the experience among MS and pose serious challenges for being implemented. One particular challenge, that affects existing crop insurance policies, results from the difficulty of enlarging the covers to include both inputs and outputs price volatility. The development of guidelines defining key terms, measurement methods, thresholds and eligibility criteria would facilitate local administrations in implementing the RMT and lower administrative costs, making the policy more attractive. Flexibility on the application of the RM policy helps addressing the issue of the institutional, economic and agricultural diversity across and within MS. Finally, farmers, administrations, and stakeholders could be better informed about the RMT, especially in terms of its scope and utility. This could be achieved in synergy with other AKIS policies.

However, there are still many issues that need to be explored and better understood. For example, the fact that the IST as it was designed was adopted by just one region in the EU even though it could cover losses from any type of risk. Therefore, additional research comparing different policy tools and their potential substitution effects is still needed.

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Appendix 1 - Risk Management in the EU's CAP 2014-2020

The EU Regulation 1305/2013 on "*support for rural development by the European Agricultural Fund for Rural Development (EAFRD)*", subsequently amended by the EU Regulation 2017/2393 (the Omnibus Regulation), forms the regulatory basis for the RMT in the CAP 2013-2020. The EU regulation establishes that support can be granted to five main risk management tools (see table A1.1). MS are responsible for avoiding overcompensation to farmers due to the application of the five RM tools in combination with other national or EU support instruments and private insurance schemes.

The regulation is implemented through the second pillar of the CAP and financial support to risk management can be voluntarily granted by each MS through the RDPs. The RDPs are structured around six Priorities. Priority 3 "Food Chain Organisation and Risk Management" has two Focus Areas. Focus Area 3A is about the organization of the food production chain (producer groups and organisations, quality schemes, promotion in local markets and short supply circuits, etc.). Focus Area 3B relates to risk prevention and management and contains, among other things, the RMT. More specifically, Article 18 of Reg. 1305/2013 is implemented through M5 of the RDPs, while articles 36 to 38 through M17.

On average, MS have allocated to Priority 3 about 10.4% (€16.1 billion, of which 9.6 from EAFRD) of the total RD planned expenditure. Three MS (Italy, Slovakia and Hungary) have allocated the higher public expenditure on Priority 3, which is above 15% of the total RDP expenditure. Only one MS (Denmark) did not activate Priority 3 at all. Within Priority 3, the average planned public expenditure per focus area was 69% to 3A and 31% to 3B[6]. Focus Area 3B received about 3% of total RD planned public expenditure. The higher public expenditure allocated to Focus Area 3B occurs in Italy (9.2%), Hungary (8%) and Germany (7.4%).

M17 was allocated with 17% of the Priority 3 planned expenditure, for a total of about €2700 million. M17 represents 54% of the planned expenditure for Focus Area 3B, while M5 counts for 43% (the remaining 3% is used for other measures including financing farm advice, knowledge transfer and training). The higher number of farms (>5%) participating in risk management schemes are in France, Italy, Belgium and Malta[7].

The use of the RMT is very fragmented across MS. Only 16 out of 28 MS have planned the adoption of the whole or part of the RMT in their RDP 2014-2020. In some circumstances, despite its adoption was planned, the RMT was never actually implemented. The high heterogeneity in the level of RMT uptake across MS has been inherited, in part, due to the nature of EU RM regulations introduced with the Health Check of the CAP from 2008 onwards. For instance, only some MS such as France, the

[6] Source: https://enrd.ec.europa.eu/sites/default/files/priority-3-summary.pdf
[7] Source: https://enrd.ec.europa.eu/sites/default/files/focus-area-summary_3b.pdf

Netherlands, Hungary and Italy supported insurance premiums and mutual funds since 2010 according to Art. 70 and 71 of Regulation (EU) No. 73/2009. Considering for example the Italian case; farmers there are not required to have certified financial statements, which has prevented the development of the IST. At the same time, there are differences in insurance demand (80% of insured are in the north of Italy) linked to the role of farmers unions and to the climatic history of the regions. The insurance companies have specialized the crop insurance products on the requests of the unions and consortiums of northern Italy, thus leaving the demand of the other regions uncovered. Also important is the case of Spain which, by political choice, continued to use national resources for risk management.

Table A1.1. Risk management tools in the EU Regulation 1305/2013

Financial support for investments (Art. 18)	**Financial contributions to insurance premiums (Art. 37)**	**Financial support for mutual funds (Art. 38)**	**Financial support for IST (Art. 39)**	**Financial support for sector specific IST (Art. 39a)**
This tool is designed for promoting risk management investments and no support is granted for loss of income. The investments covered are for: a) Preventive actions to reduce the consequences of probable natural and catastrophic events; b) Restoring agricultural land and production facilities damaged by natural and catastrophic events. Recipients of the financial support can be either individual farmers, groups of farmers, or public entities.	For insurances covering losses from adverse climatic events, environmental incidents, animal or plant diseases, and pests destroying more than 20% of the average annual production calculated over three years. Losses can be measured using biological, yield or weather indexes and compensations are paid net of an excess that varies from MS.	For mutual funds covering losses from adverse climatic events, environmental incidents, animal or plant diseases, and pests destroying more than 20% of the average annual production calculated over three years. Mutual funds have to be accredited by each MS's national authority and each MS defines the rules for the constitution and management of the mutual funds, ensuring monitoring and transparency regarding payments, attribution of responsibilities, and eligibility of farmers. Financial contribution can be used to cover the administrative costs of setting up a mutual fund and its initial capital stock, the annual payments into the fund, and the compensations to farmers.	For supporting mutual funds compensating farmers of any sector whose income dropped by more than 30% of the average annual income calculated over three years. Income losses can be measured using indexes and compensations are not linked to any specific cause of the loss of income. Compensations can cover up to 70 % of the income lost. Mutual funds have to be accredited by each MS's national authority and each MS defines the rules for the constitution and management of the mutual funds, ensuring monitoring and transparency regarding payments, attribution of responsibilities, and eligibility of farmers. Financial contributions can be used to cover the administrative costs of setting up a mutual fund and its initial capital stock, the annual payments into the fund, and the compensations to farmers.	For supporting mutual funds providing compensation to farmers in specific sectors whose income dropped by more than 20% of the average annual income calculated over three years. Income losses can be measured using indexes and compensations are not linked to any specific cause of the loss of income. Compensations can cover up to 70 % of the income lost. Mutual funds have to be accredited by each MS's national authority and each MS defines the rules for the constitution and management of the mutual funds, ensuring monitoring and transparency regarding payments, attribution of responsibilities, and eligibility of farmers. Financial contributions can be used to cover the administrative costs of setting up a mutual fund and its initial capital stock, the annual payments into the fund, and the compensations to farmers.
This support was planned in 11 EU MS: Croatia, France, Germany, Greece, Hungary, Italy, Latvia, Polonia, Portugal, Slovakia, Spain	This support was planned in 9 EU MS and 1 region: Flanders (BE), France, Croatia, Italy, Latvia, Lithuania, Hungary, Malta, Netherlands and Portugal	This support was planned in 3 EU MS: France, Italy and Romania	This support was planned in 2 EU MS and 1 region: Italy, Hungary and Castilla y Leon (ES)	

Appendix 2 - List of equations

The general nesting spatial (GNS) model can be expressed as:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{WY} + \beta_x \boldsymbol{X} + \theta \boldsymbol{WX} + \mathbf{u}$$
$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad \text{(A1).}$$

Here, $\boldsymbol{Y}$, $\boldsymbol{X}$, β_0, β_x, and $\boldsymbol{\varepsilon}$ are similar to equation (1), and $\boldsymbol{W}$ is the ($N \times N$) normalized spatial weight matrix. $\boldsymbol{WY}$, $\boldsymbol{WX}$, and $\boldsymbol{W}\mathbf{u}$ are ($N \times 1$) vectors representing the spatial lags for the dependent variable $\boldsymbol{Y}$**,** independent variables $\boldsymbol{X}$, and error term $\mathbf{u}$, while ρ, θ, and λ are scalar parameters for the spatial effects that needs to be estimated for the dependent variable**,** independent variables, and error term, respectively.

The first model that can be estimated is the spatial error model (SEM), which assumes that $\rho = \theta = 0$, and estimate the spatial effect within the error terms. The SEM can be expressed as:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \mathbf{u}$$
$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad \text{(A2).}$$

The second model that can be estimated is the spatial lag of X variables (SLX) model, which assumes that $\rho = \lambda = 0$, and estimate the spatial effect the neighbouring variables. Such that:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \theta \boldsymbol{WX} + \boldsymbol{\varepsilon} \quad \text{(A3).}$$

The third model is the spatial autoregressive (SAR) model, which is a widely used and assumes that $\theta = \lambda = 0$. The SAR model assumes that different values of the dependent variable $\boldsymbol{Y}$ depends on the neighbouring dependent values of $\boldsymbol{Y}$. This is similar to the autoregressive models in time-series regressions, where y_t depends on its lagged value y_{t-1} (Anselin and Bera, 1998: 246):

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{WY} + \beta_x \boldsymbol{X} + \boldsymbol{\varepsilon} \quad \text{(A4).}$$

A combination of the three previous models (SEM, SLX, and SAR) in equations (A2), (A3), and (A4) allows for the estimation of ρ and θ. The spatial Durbin model (SDM) assumes that only $\lambda = 0$, and estimates the spatial effects of the independent variables and the dependent variable:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{W}\boldsymbol{Y} + \beta_x \boldsymbol{X} + \theta \boldsymbol{W}\boldsymbol{X} + \boldsymbol{\varepsilon} \qquad \text{(A5).}$$

Similarly, the spatial Durbin error model (SDEM) assumes that only $\rho = 0$, and estimates the spatial effects of the $\boldsymbol{X}$ variables and the error term:

$$\begin{gathered} \boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \theta \boldsymbol{W}\boldsymbol{X} + \mathbf{u} \\ \mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \end{gathered} \qquad \text{(A6).}$$

Finally, the spatial autoregressive combined (SAC) model assumes that $\theta = 0$, and estimates the spatial effects of the dependent variable and the error term:

$$\begin{gathered} \boldsymbol{Y} = \beta_0 + \rho \boldsymbol{W}\boldsymbol{Y} + \beta_x \boldsymbol{X} + \mathbf{u} \\ \mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \end{gathered} \qquad \text{(A7).}$$

Appendix 3. GMM estimations for factors influencing Risk Management expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
	SEM	SAR	SLX	SDM	SDEM	SAC
β(**X**):						
GVA per capita	-0.114	0.005	-0.013	-0.165	-0.024	0.017
	(0.16)	(0.16)	(0.19)	(0.17)	(0.19)	(0.16)
Agricultural VA	**-0.105****	-0.058	-0.070	-0.089	-0.077	-0.049
	(0.047)	(0.046)	(0.059)	(0.055)	(0.057)	(0.045)
CAP subsidies	**-0.182*****	**-0.140****	**-0.202*****	**-0.172*****	**-0.207*****	**-0.129****
	(0.067)	**(0.064)**	**(0.070)**	**(0.066)**	**(0.068)**	**(0.062)**
Precipitation	0.084	0.080	0.082	0.108*	0.088	0.081
	(0.063)	(0.064)	(0.072)	(0.065)	(0.071)	(0.064)
Heatwave intensity	0.022	0.023	0.030	0.054	0.046	0.020
	(0.066)	(0.062)	(0.071)	(0.070)	(0.070)	(0.061)
Wind erosion	0.008	0.003	0.009	0.011	0.010	0.002
	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)
Water erosion	-0.063	-0.102	0.101	0.065	0.072	-0.102
	(0.083)	(0.077)	(0.096)	(0.092)	(0.092)	(0.076)
Land diversity	0.083	0.111	0.068	0.049	0.070	0.110
	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)
Arable land	**0.096*****	**0.094*****	0.060	**0.069***	0.060	**0.094*****
	(0.037)	**(0.035)**	**(0.041)**	**(0.038)**	**(0.039)**	**(0.035)**
Permanent crops	-0.005	-0.010	-0.016	-0.002	-0.016	-0.010
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)
Pastures	0.002	0.002	0.021	0.004	0.013	0.003
	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.029)
Agricultural diversity	0.033	0.029	0.022	0.039	0.025	0.028
	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.031)
Forest	0.016	0.029	0.046	0.063	0.053	0.031
	(0.045)	(0.043)	(0.047)	(0.051)	(0.046)	(0.043)
LFA	0.026	0.031	0.026	0.025	0.026	0.032
	(0.027)	(0.027)	(0.023)	(0.024)	(0.023)	(0.026)
RDP regions	Yes	Yes	Yes	Yes	Yes	Yes
W						
λ(**Wu**)	**0.449*****				**0.342*****	**-0.114**
	(0.10)				**(0.12)**	**(0.17)**
ρ(**WY**)		**0.447*****		**0.967*****		**0.527*****
		(0.095)		**(0.18)**		**(0.094)**
θ(**WX**)						
GVA per capita			**1.133****	0.499	0.877	
			(0.54)	(0.52)	(0.56)	
Agricultural VA			-0.137	0.075	-0.099	
			(0.14)	(0.12)	(0.14)	
CAP subsidies			**-0.583*****	**-0.169**	**-0.563*****	
			(0.20)	**(0.21)**	**(0.20)**	
Precipitation			-0.200	-0.003	-0.070	
			(0.21)	(0.19)	(0.22)	
Heatwave intensity			0.139	-0.067	0.057	
			(0.17)	(0.16)	(0.18)	
Wind erosion			-0.038	0.014	-0.005	
			(0.050)	(0.050)	(0.051)	
Water erosion			-0.328	-0.004	-0.220	
			(0.23)	(0.23)	(0.25)	
Land diversity			0.218	0.081	0.332	
			(0.48)	(0.39)	(0.47)	

(continue)

Arable land			0.046	-0.111	-0.005	
			(0.13)	(0.12)	(0.13)	
Permanent crops			**-0.120*****	-0.060	**-0.118*****	
			(0.042)	(0.041)	**(0.044)**	
Pastures			0.029	0.078	0.055	
			(0.083)	(0.082)	(0.086)	
Agricultural diversity			-0.124	-0.131	-0.127	
			(0.086)	(0.085)	(0.088)	
Forest			-0.046	-0.118	-0.089	
			(0.17)	(0.15)	(0.17)	
LFA			0.050	0.003	0.040	
			(0.066)	(0.066)	(0.069)	
RDP regions	Yes	Yes	Yes	Yes	Yes	Yes
N	1265	1265	1265	1265	1265	1265
Pseudo R^2	0.591	0.590	0.650	0.599	0.649	0.587
Wald chi^2	2195.6	1426099.5	121540.7	147143.4	1.56E+10	14458.3

SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDM = spatial Durbin model; SDEM = spatial Durbin error model; SAC = spatial autoregressive combined model.
Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < 0.01$.

Appendix 4. ML estimations for factors influencing Risk Management expenditure as % of total RD expenditure (including Other output)

	(1) SDM	(2) SDEM
β(**X**):		
GVA per capita	0.0361	0.0708
	(0.25)	(0.25)
Agricultural VA	-0.117	-0.117
	(0.078)	(0.078)
CAP subsidies	**-0.295*****	**-0.300*****
	(0.079)	**(0.078)**
Precipitation	0.0902	0.0913
	(0.071)	(0.072)
Heatwave intensity	0.0624	0.0610
	(0.077)	(0.076)
Wind erosion	-0.00287	-0.00120
	(0.020)	(0.020)
Water erosion	0.148	0.136
	(0.11)	(0.11)
Land diversity	-0.0697	-0.0731
	(0.18)	(0.18)
Arable land	**0.161*****	**0.161*****
	(0.060)	**(0.059)**
Permanent crops	-0.00978	-0.0126
	(0.016)	(0.016)
Pastures	0.0551	0.0528
	(0.042)	(0.042)
Agricultural diversity	0.0598	0.0564
	(0.040)	(0.040)
Forest	0.0418	0.0449
	(0.090)	(0.089)
LFA	0.0245	0.0221
	(0.029)	(0.029)
Other output	0.00461	0.00715
	(0.030)	(0.030)
RDP regions	Yes	Yes
W		
λ(**Wu**)	**0.203*****	
	(0.063)	
ρ(**WY**)		**0.188*****
		(0.071)
θ(**WX**):		
GVA per capita	0.994	1.027
	(0.70)	(0.73)
Agricultural VA	-0.188	-0.196
	(0.22)	(0.23)

(continue)

CAP subsidies	-0.336	**-0.453***
	(0.24)	**(0.25)**
Precipitation	0.0695	0.116
	(0.22)	(0.23)
Heatwave intensity	-0.269	-0.297
	(0.19)	(0.20)
Wind erosion	0.0425	0.0476
	(0.056)	(0.058)
Water erosion	-0.320	-0.319
	(0.23)	(0.24)
Land diversity	-0.0272	0.0920
	(0.53)	(0.55)
Arable land	0.0396	0.0590
	(0.18)	(0.18)
Permanent crops	**-0.135*****	**-0.143*****
	(0.049)	**(0.050)**
Pastures	-0.0239	-0.0230
	(0.11)	(0.12)
Agricultural diversity	-0.138	-0.138
	(0.13)	(0.14)
Forest	0.0292	0.0133
	(0.24)	(0.25)
LFA	-0.0253	-0.0286
	(0.079)	(0.083)
Other output	0.0783	0.0875
	(0.084)	(0.088)
RDP regions	Yes	Yes
N	929	929
Pseudo R^2	0.6937	0.6943
Wald chi^2	3208.41	3218.06