wildE

Climate-smart rewilding for Europe

Opportunity costs of nature restoration at the European scale

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1. Introduction

Rewilding, defined as the passive management of ecological succession, aims to restore natural ecosystem processes by reducing human intervention in landscapes (Pereira and Navarro, 2015). As a strategy for biodiversity conservation, rewilding holds the potential to enhance ecosystems with minimal direct management. However, this shift from traditional land use, particularly farmland or forestry, to a rewilded state often results in a loss of income for the land owners. This loss of income is the opportunity cost of rewilding, which represents the economic value forgone when transitioning land from productive uses, such as agriculture or timber harvesting, to a natural, unmanaged state (Adams et al., 2010). The opportunity cost of land conservation varies spatially, as the economic returns from farming or forestry depend on factors such as soil quality, climate, farm technology, and market accessibility, each of which differs across locations. This spatial heterogeneity raises the question of how to prioritize areas for nature conservation in a cost-effective manner(Armsworth, 2014; Jung et al., 2024). While a rich a literature on nature conservation planning still many approached ignore competing land uses and land competition (Jung et al., 2024). This report focuses on the opportunity costs associated with rewilding, as part of the wildE project. The objective is to estimate these costs for farmland and forest land across Europe, with a particular focus on spatial heterogeneity. An important outcome is a set of maps showing the opportunity costs of rewilding on agricultural land under different assumptions.

Understanding the opportunity costs associated with rewilding is critical for evaluating the economic trade-offs involved in nature conservation management. These costs mainly stem from the loss of economic income derived from human activities, such as farming or timber harvesting. The magnitude of these costs may depend on the degree of rewilding, i.e. the restrictions on human activities, which also influences the potential environmental gains of rewilding (Mutillod et al., 2024). A key question in this context is whether to account only for the direct loss of income or to also consider the potential ecosystem services that rewilding could provide, such as carbon storage, water protection, and recreational value. Correcting the opportunity costs for the value of such services would provide a net-opportunity costs, that in some cases may be negative as the value of increase in environmental services may be larger than the income lost. In the present report we will only focus on opportunity costs defined as the loss of income due to restrictions on economic activities. The potential benefits of rewilding and calculating of, for example, benefit-cost ratios will be addressed in Task 4.3 of the project. Estimating the opportunity costs without considering side effects will also allow a more transparent calculation of costs. These estimates may then serve as inputs, together with other types of spatial data, to multicriteria analyses for identifying suitable locations for rewilding (Kloibhofer et al., 2025).[1]

For the estimation of opportunity costs, various methodological approaches have been used (Naidoo & Adamowicz, 2006). One common method involves calculating the reduction in revenue resulting from the cessation of productive activities, such as the decline in the sales value of agricultural products minus saved input costs. Alternatively, market rental prices of land for farming or other economic activities can serve as a proxy for opportunity costs. Land prices reflect the capitalization of future rents from productive use and can therefore also be used a s measure. However, using land prices is complicated by the fact that land values also incorporate amenity values—such as aesthetic and recreational uses—which may actually increase with rewilding (Armsworth, 2014; Lautrup et al., 2023). Furthermore, land prices may be influenced by future development expectations and speculation, further challenging the use of land prices as a measure of opportunity costs.

For agriculture, opportunity costs can be loss of farm profit by changing land use, i.e. difference between all output values and input expenses, excluding the costs of owning or renting land[2]. However, an important question is how to treat financial transfers, i.e. tax and subsidies. These are normally not included in an economic analysis, for example a social cost-benefit analysis. (Schou et al., 2021). On the other hand, they would be included in a financial cost-benefit analyses from a farmer or government budget. This issue is particularly relevant in Europe, where subsidies from the Common Agricultural Policy (CAP) account for a significant portion of farm income.

As explained above, opportunity costs should theoretically reflect the remuneration of land under the current land use. However, in practice, this measure is often not the most relevant input for land-use conservation decision-making. Therefore, in the present study, we present different measures of opportunity costs. We apply different definitions of farm value added (VA), which is defined as the difference between the value of production and input expenses. The measures differ with respect to whether they account for taxes and subsidies, capital costs, and labour costs. Which measure is most appropriate depends on the objective and context in which opportunity costs are used.

First, it matters whether we are conducting an economic analysis from a social point of view or a financial analysis from the perspective of farmers or government. For example, by including taxes and subsidies, the

[1] We recognize that determining what to include in the calculation of opportunity costs is not always clear-cut. For example, a farmer giving up part of their farmland for nature conservation may still retain the right to hunt on adjacent areas. The hunting value of these areas may increase. In this case, one could argue that the loss of income from ceasing farming on a portion of the land should be adjusted to account for the increased hunting value on the non-conserved land.

[2] The cost of owning or renting land is not included, as our objective is to estimate the value generated by the production factor land. Note that, under a perfect land market, with profit-maximizing farmers and no externalities, we would expect economic profit to be zero once all costs, including the cost of land, have been subtracted from revenue.

analysis better reflects the financial impact of rewilding, i.e. lost subsidies or saved taxes from the landowners' perspective, as well as impacts on the public budget. Secondly, whether to account for capital costs and labour costs depends on whether one assumes that the labour and capital employed in agriculture have alternative uses if they are not used in agriculture.

For forest land, where revenue depends much less on subsidies, we apply a different approach in which we estimate the net present value of future production, accounting for timber production value, harvest costs, standing timber stock, and the capital costs associated with the long time horizon of timber production.

In the following section, we expand our discussion of the conceptual framework for estimating opportunity costs and review the literature on their estimation. The next section presents our methodology for estimating opportunity costs for agricultural and forest land. Finally, we present and discuss the opportunity cost maps developed in the project and explain how these can be integrated into the wildE land-use modelling framework to estimate future opportunity costs under alternative socio-economic and climate scenarios.

2. Literature review

In this section, we review the existing literature on the estimation of opportunity costs for conservation efforts, with a particular focus on spatially explicit approaches. While rewilding is a specific form of conservation, our emphasis is broader, encompassing nature conservation on agricultural and forest land. This is because the economic methods used to estimate conservation costs are largely similar, and only a limited number of studies have directly addressed the economics of rewilding (Faure, Levrel, and Quétier, 2024).

Concepts

Naidoo and Adamowicz (2006) remain foundational in this area. They emphasize that accounting for spatial heterogeneity in conservation costs can significantly increase the efficiency of conservation planning. Their key focus is on solving the cost-effectiveness problem: how to achieve conservation targets (e.g., protecting a minimum portion of each species' habitat) at the lowest possible cost. They classify conservation costs into five categories: acquisition, management, transaction, damage, and opportunity costs. While acquisition costs may reflect opportunity costs, exceptions arise, such as conservation on public land, where market prices may not be informative. Two main methods have been applied for estimating opportunity costs:

- **Land market-based approaches**, using farmland prices (e.g. Ando et al., 1998; Strange et al., 2006; Rodewald et al., 2019), often with hedonic pricing models or machine learning tools (Nolte, 2020).

- **Productivity-based approaches**, using crop yields and prices (e.g. Ando et al., 1998; Polasky, Camm, and Garber-Yonts, 2001; Polasky et al., 2008; Bryan, King, and Ward, 2011; Schleupner and Schneider, 2013; Cunningham et al., 2021).

Land prices can embed various expectations, including future subsidies or potential development value (Goodwin, Mishra, and Ortalo-Magné, 2003). Sinden (2004), for example, links farmland value to natural vegetation coverage to estimate the cost of increasing biodiversity on farm land.

Productivity-based methods are frequently used in global and forestry studies (Armsworth, 2014). These rely on gross revenues or margins (e.g. Carwardine et al., 2008; Polasky et al., 2008), while capital and labor inputs are often neglected. Naidoo et al. (2006) highlight the importance of accounting for time dynamics and feedback effects: future investment in intensive land use, or increasing scarcity of productive land, can influence opportunity costs over time (Costello and Polasky, 2004; Armsworth et al., 2006).

Cost estimation techniques in practice

Armsworth (2014) reviews the wide variability in empirical cost estimation methods. Many studies use proxies like population density or GDP; others apply more refined indicators such as crop revenue. He notes that cost estimates aggregated at the county level often fail to capture local heterogeneity in land productivity. Since protected areas are frequently targeted toward specific land types – such as wetlands – this can introduce systematic bias, leading average cost estimates to deviate from the actual opportunity costs of conservation. Moreover, many studies are criticized for extrapolating opportunity costs using estimated transfer functions without empirical validation – exceptions being, for example, Naidoo and Adamowicz (2006) and Bryan, King, and Ward (2011). Additionally, these studies often assume constant marginal costs, despite the possibility that marginal costs may rise or fall with the extent of protected areas. It is therefore recommended that cost assessments clearly articulate their underlying assumptions and incorporate sensitivity analyses to test their robustness.

Spencer et al. (2024) systematically review 20 studies and note that most estimate opportunity costs using land prices, land rents, or agricultural production data. Adams (2024) revisits the previous reviews of cost assessment in conservation planning (e.g. Naidoo et al., 2006; Armsworth, 2014), suggesting that cost assessment has not played an important role in conservation practice and recommending improvements to the planning procedure. This includes identifying the groups impacted by and paying for the conservation, using sufficiently high-resolution data, and using modelling approaches or stated preference methods if high-resolution data is unavailable, in order to account for temporal aspects (Yoon and Armsworth, 2022), including feedback effect on land prices (Armsworth et al., 2006). He also raises the issue of asymmetric information on costs, suggesting that reverse auctions could be used to reveal landowners' true opportunity costs.

Case studies: From global to regional scales

A key study closely related to the present research is Spencer et al. (2024), who estimate opportunity costs for the proposed Trans-European Nature Network. Opportunity costs are based on average regional or national land rents (cropland and grassland) or timber harvest values (forest land). Spatial heterogeneity is introduced by allocating these average values using 5 arc-minute grid-scale agricultural yield data (Yu et al., 2020) and spatial forest yield data (Verkerk et al., 2015) to obtain spatial heterogeneity. Their cost maps have informed spatial conservation planning across Europe (Visconti, O'Connor, and Beher, 2024).

Strassburg et al. (2020) provide a global-scale counterpart, estimating restoration costs as net present values (NPV) of foregone agricultural profits, including implementation costs and using models like GAEZ and IMPACT. Fastré et al. (2021) use agricultural suitability as a cost proxy, while Doelman et al. (2020) incorporate feedback on land rents under various climate scenarios using the IMAGE framework and GTAP data.

At the national level, Naidoo and Adamowicz (2006) estimate opportunity costs in forest conservation by linking land conversion probabilities with output values. In Denmark, studies like Lundhede and Thorsen (2017) and Schou et al. (2021) use forest growth models and farm accounting statistics to estimate opportunity costs of biodiversity conservation or rewilding.

Other regional studies consider partial land use change or management constraints (Mewes et al., 2015; Ruijs et al., 2015), while Golub et al. (2009) use general equilibrium models to account for global competition between land uses.

Stated preference approaches and other approaches

In contrast to opportunity cost models based on observed productivity, some studies predict potential rewilding areas from socio-spatial indicators like accessibility or night lighting (Ceausu et al., 2015). Others use stated preference methods – such as contingent valuation or choice experiments – to assess landowners' willingness to rewild against an economic compensation (Granado-Díaz, Villanueva, and Gómez-Limón, 2022).

Lessons for future research

Although several European (e.g. Bladt et al., 2009; Spencer et al., 2024) and global (e.g. Naidoo and Iwamura, 2007; Strassburg et al., 2020) studies estimate spatially explicit opportunity costs of conservation, few consider the role of agricultural subsidies or the assumptions surrounding capital and labor costs (Bateman et al., 1999). This is a key gap that this study addresses.

In the present research, we combine simulated agricultural yield data (Yu et al., 2020) with detailed farm-level accounting information from the FADN database. This allows us to test different assumptions about costs and subsidies. By using individual, georeferenced farm data from a French case study, we provide an empirical complement to European-scale assessments based on aggregated FADN regions.

3. Methodology

Farmland opportunity costs

This section details the empirical strategies for estimating farmland opportunity costs using two distinct models: a France-level model linking value added (VA) to soil, climate, and price data, and an EU-level model linking VA to crop productivity and prices. Key methodological innovations include the use of a correlated random effects (CRE) framework to address time-invariant soil variables in France and country fixed effects to capture unobserved heterogeneity in the EU model. Below, we explain these approaches, refine the models, and justify their application.

Value Added specifications

Opportunity costs represent the economic trade-off of diverting farmland from agricultural production to alternative uses, such as rewilding. While farm profit (revenue minus costs) is a common proxy, subsidies and taxes distort this measure, particularly in Europe where subsidies from the Common Agricultural Policy (CAP) constitute around 58% of farm income (before tax) (Chatellier and Guyomard, 2023). To address this issue we apply different value added (VA) measures which reflect different assumptions about subsidies, capital, and labour costs. VA is a metric to isolate the net economic contribution of farming activities. We define four different VA measures to capture distinct economic dimensions (Table 1). Each step refines the estimate by incorporating additional costs, which will allow us to calculate opportunity costs under different scenarios about costs.

- **Gross Value Added (GVA)**

The most basic measure of VA is Gross Value Added (GVA), which calculates the difference between agricultural production and intermediate input expenses (*e.g.*, seeds, fertilisers, plant protection products, fuels, energy, etc.). This provides an initial estimation of the farm's net economic contribution by excluding costs related to capital (machinery, buildings, land), labour, and financial transfers like subsidies and taxes.

$$GVA = Production - Intermediate\ inputs - Insurance \tag{1}$$

This metric captures the immediate surplus after variable costs (e.g., seeds, fertilizers, fuel, etc.), providing an upper-bound estimate of farm profitability. However, fixed costs such as labor, capital depreciation, and land-related expenses are not subtracted. As a result, this measure primarily reflects the short-term economic contribution of farming activities without accounting for the full cost structure of the farm. However, this may be a relevant measure in situations where farmers have no alternative use for their buildings and machinery, or alternative employment opportunities. It has often been the measure used in conservation planning (e.g. Carwardine et al., 2008; Polasky et al., 2008).

- **Value Added with Social Transfers (VAst)**

Value Added with Social Transfers (VAst) adjusts GVA by incorporating the effects of financial transfers. We add subsidies and subtract taxes to reflect the social and financial support received by farms. This measure is particularly useful for understanding the economic implications of rewilding for farm income, as it includes the financial losses farmers might face if rewilding policies reduce their ability to receive these transfers (Bateman et al., 1999; Schou et al., 2021).

$$VAst = GVA + Subsidies - Taxes \tag{2}$$

VAst reflects the policy impacts, such as subsidies from the CAP and other social transfers, while also accounting for taxes. This measure captures the landowner's income loss due to rewilding, making it directly relevant for designing compensation schemes. By showing the net financial impact, VAst provides a clearer picture of the financial losses a farmer would experience, thus informing policies on economic compensation and support for landowners affected by land-use changes like rewilding. However, it is also important to consider the perspective adopted and the specific features of the policies in place. If the economic analysis is carried out from a national point of view, subsidies received from the EU budget may be considered as a real economic transfer, especially if it is assumed that there is no direct link between the national contribution to the EU budget and the CAP subsidies received. Furthermore, farmers may remain eligible for certain subsidies after giving up agricultural production on their land. In this case, GVA should not be adjusted for subsidies, since the farmer is not actually losing them.

- **Value Added Including Capital (VAcap)**

By incorporating the depreciation of farm assets, Value Added Including Capital (VAcap) provides a measure in which the costs of maintaining capital are subtracted. This corresponds to a long-term perspective, in which capital can be adjusted to the new land use and farmers therefore do not need to maintain or replace agricultural capital after rewilding.

In the short run, however, farmers may still incur capital costs, as buildings and machinery are partly sunk costs, i.e. their value cannot necessarily be recovered by selling them on a market. In the long run, once capital is fully adjusted to the new situation, the loss is not only revenue minus variable costs, but also includes avoided fixed capital costs. This reduces the calculated opportunity costs of rewilding.

$$VAcap = VAst - Capital \tag{3}$$

VAcap accounts for long-term asset depreciation, such as machinery, buildings, and other farm infrastructure. In the context of rewilding, this measure becomes particularly relevant, as transitioning to rewilded land may reduce the need for reinvestment in agricultural capital. VAcap captures this trade-off by factoring in the depreciation of assets that would no longer require maintenance or replacement, offering a more comprehensive view of the long-term economic implications of rewilding on capital expenditures.

- **Value Added Including Labour (VAlab)**

Finally, Value Added Including Labour (VAlab) accounts for the full costs of farm operation by incorporating both capital and labour expenses. This measure comes closest to the remuneration of the land factor in production.

$$VAlab = VAcap - Labour \tag{4}$$

VAlab represents the residual value after accounting for all production costs, including labour expenses such as wages and social security contributions. By capturing the net economic value after all production inputs (except the cost of owning or renting land), VAlab provides an indication of the long-term financial implications of rewilding, assuming that labour can find alternative employment and that capital is fully adjusted to the new situation.

Table 1: Value added definitions and policy applications

VA type	Components	Policy use
Gross Value Added (GVA)	Production − Variable Inputs	Baseline productivity estimation – short-term perspective
Value Added with Social Transfers (VAst)	GVA + Subsidies − Taxes	Compensation design (landowner income)
Value Added Including Capital (VAcap)	VAst − Capital Depreciation	Long-term asset maintenance trade-offs (landowner income)
Value Added Including Labour (VAlab)	VAcap − Labour Costs	Long-term perspective with capital and labour adjustment (landowner income)

Econometric approach

We assume that farmland value added (VA) depends on a number of key factors, such as input and output prices, soil fertility, climate conditions, and technology, including crop productivity. Since crop productivity is likely correlated with both soil fertility and climate conditions, we estimate two separate models to address this issue.

- First approach. We regress farmland VA on input and output prices, soil fertility, and climate conditions. This model captures the direct impact of these variables on VA while accounting for their potential correlations.
- Second approach. We regress farmland VA on input and output prices and crop productivity. This method isolates the effect of productivity on VA, ensuring that the relationship between farm output and economic performance is examined independently from soil fertility and climate conditions.

The advantage of the first approach is that it allows opportunity cost predictions to be based on basic environmental variables—such as soil and climate—that are independent of farmers' choices regarding crops and management practices. As such, this approach provides an estimate of the underlying potential of land to generate value in agricultural production. In the second approach, environmental conditions are implicitly captured through the productivity measure. Specifically, we use wheat and barley yields (yield per hectare) as indicators of location-specific productivity. The advantage of this approach is that it allows us to assess how opportunity costs may change under future scenarios affecting crop productivity. This is one of the reasons we selected this approach for European-scale modelling of opportunity costs. A second motivation is the limited availability of spatially explicit farm accounting data at the European scale due to data privacy constraints. We only had access to location-specific farm data for France, through secure access procedures, which allowed us to link farm outcomes to local soil and climate data. Nevertheless, we implemented both approaches. While the final European opportunity cost maps are based on the second approach, applying both approaches allows a comparison of results for France, where the first approach could also be implemented.

To model the determinants of farmland VA, we employ two distinct econometric approaches depending on data availability and regional scope, using the Correlated Random Effects (CRE) framework (Mundlak, 1978; Wooldridge, 2010) It is important to note that we rely on a reduced-form econometric model; that is, we do not explicitly model farmers' decisions under a structural utility- or profit-maximising framework. In principle, a structural model would be preferable for modelling farmers' behavioural responses endogenously under changing framework conditions (e.g. policies or climate). However, our primary objective is to characterise the spatial variability of opportunity costs, which is largely driven by environmental conditions. Given the European scale of the analysis, and the substantial heterogeneity in farming systems and behaviour across regions, we consider a reduced-form approach to be more robust and feasible for deriving consistent spatial predictions.

Correlated Random Effects (CRE) Approach

The Fixed Effects (FE) model is a widely used approach in panel data analysis for controlling unobserved heterogeneity across entities (e.g. farms, firms, or countries) that may be correlated with explanatory variables. This model assumes that each entity has unique, time-invariant characteristics (e.g., management practices, political attitudes, or cultural norms) which can influence both the dependent variable and the regressors. These characteristics are often unobserved and difficult to measure directly.

By introducing entity-specific intercepts (α_i), the FE model accounts for this unobserved, time-invariant heterogeneity. It focuses on within-entity variation over time, ensuring that the estimated effects of the regressors are not biased by omitted variables that are constant across time. However, this comes with a trade-off: time-invariant regressors are also removed from the estimation because they are perfectly collinear with the entity-specific intercepts. This presents a major limitation when important variables – such as soil quality or topographic characteristics – remain constant over time but are nonetheless crucial for explaining outcomes like agricultural productivity or conservation costs.

To address this limitation, the Correlated Random Effects (CRE) model, introduced by Mundlak (1978) and extended by Wooldridge (2019), offers a more flexible alternative. The CRE model allows researchers to estimate the effects of both time-varying and time-invariant variables while still accounting for unobserved heterogeneity. It does so by including group-level averages (i.e., individual means) of the time-varying regressors in the regression. This inclusion controls for the correlation between the explanatory variables and the unobserved individual effects, thereby enabling unbiased estimation of coefficients for time-invariant variables.

Specifically, by including entity-level averages – such as average prices, productivity, or climatic conditions – the CRE model mimics the control offered by fixed effects while retaining time-invariant regressors like soil characteristics. This hybrid structure preserves the robustness of the FE approach with respect to endogeneity and omitted variable bias, while extending the model's explanatory scope.

The CRE model is particularly well-suited to analysing farmland value added (VA), where a combination of stable structural variables (e.g., soil fertility) and dynamic influences (e.g., climatic variability, market prices) must be considered. In this study, we estimate two CRE models reflecting the regional scope: one for France-level municipal data, and one for EU country-level data. Each model is tailored to the respective data structure, capturing the influence of key explanatory variables such as input and output prices, crop productivity, climate conditions, and soil quality on farmland VA.

At the EU country level, the CRE model also enables the inclusion of country-specific fixed effects, helping to account for differences in agricultural policies, market conditions, and environmental regulations. Moreover, by avoiding the incidental parameters problem commonly associated with traditional fixed effects in short panels, the CRE approach ensures more efficient estimation while preserving control over unobserved heterogeneity (Wooldridge, 2019; Ragasa, 2020; Musumba et al., 2022).

First approach: modeling VA based on soil, climate, and prices

The first approach focuses on capturing local variability in agricultural practices using farm-level data. It incorporates time-varying variables (e.g., input and output prices, climate conditions) and time-invariant variables (e.g., soil fertility) through the CRE approach. We regress different farmland VA measures on input and output prices, soil fertility, and climate conditions. This model captures the direct impact of these variables on VA while accounting for their potential correlations between unobserved farm effects and regressors. The model is specified as follows:

$$VA_{it} = \beta_{1t}OP_t + \beta_{2t}IP_t + \beta_{3i}Soil_i + \beta_{4i}Climate_{it} + \gamma_1\overline{OP}_i + \gamma_2\overline{IP}_i + \gamma_3\overline{Climate}_i + \varepsilon_{it} \quad (5)$$

where VA_{it} is the value added for farm i at time t, OP_t and IP_t represent output and input prices, respectively, $Soil_i$ is the time-invariant soil characteristics, $Climate_{it}$ represents time-varying climate conditions, the terms $\overline{OP}_i$, $\overline{IP}_i$ and $\overline{Climate}_i$ are the Mundlak averages of the respective variables, which control for unobserved heterogeneity, and ε_{it} are farm-specific fixed effects and the error term, respectively.

Second approach: modeling VA based on productivity and prices

The second approach focuses on regressing farmland VA on input and output prices and crop productivity. This method isolates the effect of productivity on VA, ensuring that the relationship between farm output and economic performance is examined independently from soil fertility and climate conditions. It expands the analysis to multiple countries, introducing country-specific fixed effects. This model accounts for cross-country differences in agricultural policies, market conditions, and environmental factors that impact farmland value added across countries.

$$VA_{it} = \beta_{1t}OP_t + \beta_{2t}IP_t + \beta_{3i}Productivity_{it} + \gamma_1\overline{OP}_i + \gamma_2\overline{IP}_i + \gamma_{3i}\overline{Productivity}_i + \delta_c country_c + \varepsilon_{it} \quad (6)$$

where $Productivity_{it}$ represents crop productivity, and $country_c$ is a set of dummy variables for each country to capture fixed effects at the country level.

Farmland data description

France-level data – First approach

Climatic data

We used SAFRAN climatic data provided by Météo-France, accessed via the SICLIMA platform developed by AgroClim-INRAE (Bertuzzi and Clastre, 2022). The SAFRAN data comprises daily re-analysed climate variables at the grid cell level, with each grid cell covering an 8 km x 8 km area across entire France, representing approximately 9,000 grid cells. This dataset integrates daily local meteorological observations from within each grid cell is updated annually to ensure accuracy and currency. For this study, we focused on two key variables – temperature and rainfall – during the growing season, defined as February to July (Bareille and Chakir, 2024). The climatic data cover the period from 2010 to 2022, providing robust temporal coverage for analysing recent climate trends and their potential impact on the study area.

Soil data

Soil characteristics were derived from data provided by the Soil Quality Measurement Network (RMQS) (Institut National de la Recherche Agronomique et al., 2021). Since its introduction in 2000, the RMQS has aimed to assess and monitor soil quality across France over the long term. The network comprises 2,240 monitoring sites evenly distributed across the country on a 16 km x 16 km grid. At the centre of each grid cell, soil samples, measurements, and observations are taken every fifteen years. Soil quality is evaluated by analysing the physical, chemical, and biological properties of the soil, identifying sources of diffuse contamination, and examining the history of land use and management practices at each site. For this study, we selected the soil characteristics most relevant to biomass production, including clay, fine silt, fine sand, nitrogen, phosphorus, potassium, magnesium, and the carbon-to-nitrogen ratio (Adhikari and Hartemink, 2016; Greiner et al., 2017).

Economic data

We used data from the Farm Accountancy Data Network (FADN), which includes information on production costs and sales values. The FADN is an annual survey, harmonised at the European Union (EU) level, that collects detailed accounting and technical-economic data from a representative sample of farms (Piet et al., 2020). The network was established following the 1965 regulation adopted by the Council of Ministers of the European Economic Community (EEC) to monitor the economic performance and income of agricultural holdings across the original six Member States (Carles, 1969). In France, the FADN has been operational since 1968, collecting accounting data from approximately 7,000 farms annually. These farms are categorised based on their technical and economic orientations, such as meat production, dairy farming, cereal cultivation, fruit and vegetable farming, and viticulture. Some farming systems, like cereal cultivation, require extensive land areas, while others, such as pig farming, require less, or no land. For this study, we focused specifically on crop farms that rely on land area, where soil and climatic conditions directly influence production. Furthermore, livestock farms may potentially continue their production even if land is rewilded—for example, by purchasing fodder. Note that the cereal-producing farms also engage in other activities, such as permanent crops, horticulture, and livestock; however, their contribution to farm revenue is smaller compared to cereal crops.

Access to confidential data, used in the present study, has been made possible within a secure environment offered by CASD – Centre d’accès sécurisé aux données (Ref. 10.34724/CASD). This dataset was employed to calculate the value added by farms between 2010 and 2022. To express these figures in constant currency, we deflated them using the 2015 consumer price indices provided by the French National Institute of Statistics and Economic Studies (INSEE). Additionally, we used the input and output price indices provided by INSEE. The analysis is based on an unbalanced dataset covering the period from 2010 to 2022.

Data merging principles

To predict the opportunity costs of rewilding agricultural soils, we integrated multiple datasets. The first step involved spatial processing of the data using QGIS. Since not all municipalities engage in crop production, we used the Corine Land Cover Map to distinguish cropland from other land uses, such as urban areas, lakes, and grasslands. First, we cross-referenced the boundaries of French communes with the 2018 Corine Land Cover Map to identify areas within each commune where agriculture, specifically arable farming, is practised. We focused exclusively on arable land to align with the cereal-producing farms captured in the FADN dataset, resulting in a spatial fragmentation of communes based on arable land areas. Table 2Table 2 presents the number of municipalities by land use category, along with descriptive statistics on land area (in hectares). It is worth noting that, in 2010, metropolitan France comprised 36,570 municipalities. A total of 21,320 municipalities had both grassland and cropland.

Table 2: Descriptive statistics of land uses

Variable	Municipalities	Mean (ha)	Std. Dev.	Min	Max
Cropland	28437	539.259	596.862	0.0000367	27625.146
Permanent Crop land	5129	254.024	369.154	0.0000144	4300.11
Grassland	27091	312.29	423.629	0.0000205	5925.781
Mixed Crop land	29208	242.205	346.286	0.000128	6012.581
Vineyards	3681	305.447	389.379	0.0000484	4249.877

Next, we overlaid this arable land data with climate data grids, allowing us to assign SAFRAN climatic data to each arable plot, ensuring spatial consistency between the different datasets. Finally, we incorporated soil data from the RMQS network. Since the RMQS data points are spatially discrete, we employed a nearest-neighbour attribute join to assign soil characteristics to each arable plot based on the closest available RMQS measurement point.

Descriptive statistics

Table 3 shows the descriptive statistics of the data used for modeling the opportunity costs of farmland in France. We observe that the different value-added measures have a large standard deviation. We also see that the mean of GVA is almost three hundred euros less per hectare than VAst, which accounts for subsidies and taxes. The lowest value is, as expected, for VAlab, where we have adjusted for capital and labour costs.

Table 3: Descriptive statistics of the dataset (obs.: 19,745; number of farms: 3,236)

	Variable	Unit	Mean	Std. Dev.	Min	Max
Value added	VA	€/ha	763.642	1820.555	-3200.971	90466.117
	VAst	€/ha	1041.99	1835.4	-3334.927	98393.523
	VAcap	€/ha	725.478	1450.431	-4237.507	72179.203
	VAlab	€/ha	585.931	863.043	-5959.007	40295.422
Prices index	Input Price	-	103.783	9.591	92.3	135.8
	Cereal Price	-	116.231	26.692	91	197.6
Climate variables	Rainfall	mm/year	1.896	0.536	0.446	5.118
	Temperature	°C/year	12.665	1.325	7.699	17.842
Soil characteristics	Clay	g/kg	250.889	121.777	6	815
	Silt	g/kg	238.467	87.597	1	500
	Sand	g/kg	131.056	106.845	3	722
	Nitrogen	g/kg	1.667	0.953	0.04	7.903
	Phosphorus	cmol+/kg	0.072	0.056	0.001	0.319
	Potassium	cmol+/kg	0.434	0.268	0.01	2.15
	Magnesium	cmol+/kg	0.866	0.99	0.02	12.4
	C/N	-	11.036	3.373	5.14	43.571

EU-level data - Second approach

In the European analysis, wheat and barley yields were used as predictors of crop productivity. Wheat and barley were selected because they are two of the most widely grown and economically significant cereal crops in the European Union. Wheat continues to play a central role in both domestic consumption and exports. Barley is also crucial, primarily used for animal feed, brewing, and other industrial applications. These crops therefore provide a broad perspective on the economic dynamics of farmland value added (VA) in the region. Focusing on these two crops allows for a generalisable analysis of the relationship between productivity and farmland VA, as wheat tends to perform better in temperate climates with well-balanced soils, while barley is more resilient to harsher conditions. However, to assess the sensitivity of this choice, we also estimate models using wheat yields only and barley yields only, respectively.

Date sets for estimation

We combine the European Union FADN (see description above) and the input and output price indices from the Eurostat website. As mentioned, we retain two crops: wheat and barley productivity (Table 4), as productivity indicators for crop farms. The mean values are slightly higher for Europe than for France (Table 3), but the same pattern holds: accounting for subsidies and taxes significantly influences the value added, and the standard deviation is high.

Table 4: Descriptive statistics (obs: 235,507)

Variable	Unit	Mean	Std. Dev.	Min	Max
GVA	€/ha	662.951	1260.836	-142230.83	125192.11
VAst	€/ha	981.208	1313.422	-142127.56	124559.06
VAcap	€/ha	704.763	1168.63	-142415.94	123918.99
VAlab	€/ha	600.472	994.031	-142415.94	110228.66
Wheat	tonnes/ha	5.693	2.15	.007	20
Barley	tonnes/ha	5.065	1.973	.01	15
Input price index	-	104.6	8.559	85.32	142.01
Output price index	-	105.541	17.52	73.23	181.17

Note: The FADN variables used to calculate value added (VA) in this study are as follows: SE131 for Total Value of Output, SE025 for Utilised Agricultural Area (UAA), SE275 for Total Intermediate Consumption, IINS_V for Agricultural Insurance, SE600 for Balance of Subsidies and Taxes, SE360 for Depreciation of Capital Assets and SE370 for Total Wages and Social Security Charges

Data sets for prediction

To estimate farmland opportunity costs across the EU, we integrated gridded biomass-based crop yield data (measured in kg/ha) with country-specific input and output price indices. Crop yield data was sourced from the MapSPAM v2 dataset (Yu et al., 2020), which offers spatially detailed yields at a 10 km resolution for 42 crop types (Spencer et al., 2024). For this analysis, we focused on two crops widely cultivated in Europe: wheat and barley. To account for economic factors influencing opportunity costs, we integrated country-specific unit input and output price indices. These indices were gathered from publicly available EU statistics, such as Eurostat and national agricultural reports. The input price index reflects the cost of factors of production (e.g., fertilizers, labor, machinery), while the output price index represents the average price received by farmers for their cereal yields. Both indices are essential for adjusting the crop yield data to reflect economic realities and regional variations in production costs and market prices.

Forest land opportunity costs

For forest land, we do not have access to accounting statistics for forest owners. We therefore applied an alternative approach based on an ecological–economic simulation model. Bastit (2023) and Mohr et al. (2025) recently employed Monte Carlo simulations to evaluate the historical and future market-based costs of natural disturbances affecting four major commercial forest species at the European scale, under the assumption of constant forest management[3]. In the following, we describe the simulation approach and the dataset used.

European forests are divided into a large number of pixels (denoted as p) of resolution 16 x 16 km. We treated each pixel as a forest stand following Knoke et al. (2021). Although each stand can encompass multiple species and age classes, we disregarded interactions among them. Such interactions depend on spatial dynamics

[3] This work was carried out under the guidance of Felix Bastit (BETA) and Johannes Mohr (TUM). The final results presented here are based on a modified version of the script used in Mohr et al. (2025).

occurring at a scale much finer than the pixel resolution. Consequently, diversity in species and age distribution does not exert positive or negative effects. Each age class of each species is assumed to act independently, as if occupying its own allocated area. Specifically, within each pixel, every age class and species is treated as a pure, even-aged stand during each time period. We also assumed that the pixels are independent and do not influence one another, making the underlying simulation process strictly linear with respect to spatial extent.

The European Forest Value (EFV) is calculated as the sum of local forest values ($FV_{s,p}$) for each species s across all pixels, multiplied by the corresponding forest area $A_{s,p}$ of species s in pixel p.

$$EFV_{s,p} = \sum_{p \in Europe} \sum_{s \in species} A_{s,p} \times FV_{s,p} \tag{7}$$

We observe that the assessment problem of determining the European Forest Value (EFV) is equivalent to calculating $FV_{s,p}$ for each tree species across all European pixels. We assume that $A_{s,p}$ is fixed and does not change over time and scenarios, meaning that the European forest cover maintains the same spatial distribution of forest species in each scenario.

The Forest Value of pixel p corresponds to the sum of discounted cash flows $\left(CF_{t,p}\right)$ over an infinite time horizon at each time t. For practical purposes, the sum is restricted to times less than T, which is not detrimental if T is sufficiently large and δ_t, the discount factor, decreases rapidly enough towards zero.

$$FV_{s,p} = \lim_{T \to +\infty} \sum_{t=0}^{T} CF_{t,p} \times \delta_t \tag{8}$$

The main source of the cash flow $CF_{t,p}$ at each period t, for species s and pixel p, is the regular harvest $RH_{t,s,p}$, which occurs when a portion of pixel p reaches its rotation period $\tau_{s,y}$. The rotation period $\tau_{s,y}$ primarily depends on the timber species and the productivity of the pixel (the choice of rotation period is explained later). The cash flow is therefore the difference between timber sale revenues (i.e. stumpage price $p_{a,s,y}$ multiplied by volume $v_{a,s,y}$) and planting costs PC_s. These revenues are summed over all ages greater than the rotation period assuming a maximum forest age of 250 years.

$$RH_{t,s,p} = \sum_{a=\tau_{s,y}}^{250} S_{a,t,s,p} \times \left(p_{a,s,y} \times v_{a,s,y} - PC_s\right) \tag{9}$$

The list of variables used in the model is presented in Table 5. presents the variables used in the model.

Table 5: List of variables in the model

Variables	Unit	Description
EFV	€	Expected European Forest Value
$FV_{s,p}$	€/ha	Expected Forest Value for specie s of pixel p
$A_{s,p}$	ha	Forest area of specie s on pixel p
T	years	Duration of the simulations
δ_t	∅	Discount factor at time t
$CF_{t,p}$	€/ha	Expected cashflow at time t for pixel p
$RH_{t,s,p}$	€/ha	Expected revenues from regular harvest at time t for pixel p
$S_{a,t,s,p}$	%	Share of the area of species s on pixel p in age class a at time t
$v_{a,s,y}$	M^3/ha	Timber volume at age a for specie s, yield y
$p_{a,s,y}$	€/m^3	Price of timber at age a for specie s, yield y
PC_s	€/ha	Planting costs for specie s
$\tau_{s,y}$	years	Rotation period for specie s, yield y

The final aspect to address in this approach is capturing the dynamics between different age classes, specifically how the forest area transitions from one age class to another over each period. To achieve this, we employed a standard matrix-based model that reallocates forest area at each time step. At the end of each period t, the portion of $S_{a,t,s,p}$ (*i.e.*, the share of pixel p and species s with age a) that is harvested is transferred to $S_{0,t+10,s,p}$ in the next period, indicating a return to its initial state, with the same species s replanted. The remaining portion of $S_{a,t,s,p}$ that is not harvested is moved to the next age class, $S_{a+10,t+10,s,p}$, for the subsequent period.

We applied this approach to four commercial tree species – Norway spruce, Scots pine, common beech, and oak – which together represent 74% of the European growing stock of timber (FOREST EUROPE, 2020). These species disproportionately contribute to the economic value of temperate forests in Europe. For instance, Hanewinkel et al. (2013) estimated that the economic value of Norway spruce alone accounts for 45% of the total market value of European forests. Other species, such as silver fir and Douglas fir, are also profitable but currently represent a small share of the European forest portfolio, each accounting for less than 2% of the total European forest area. In contrast, birch, which is the fifth most prevalent species (representing 7% of the European growing stock), currently has a marginal economic performance on a per-hectare basis. This work required multiple datasets which are explained in the following sections.

Ecological input data

Forest area and tree species

A statistical mapping of tree species across Europe at a 1x1 km scale was conducted by Brus et al. (2012). They mapped the distribution of 20 tree species in 29 European countries. Their analysis was based on the National Forest Inventory (NFI) data from 13 countries and extended to the remaining 16 countries using ICP[4] Level I data, employing a multinomial multiple logistic regression model alongside small-scale variables such as soil data, biogeographical maps, and bioindicators. The study also provides forest area estimates aggregated at the European level for the different species (Table 6). We aggregated these to obtain the forest area for each species and pixel within the European grid. Only 34% of the total European forest area – representing 16 other tree species – are excluded from our analysis.

Table 6: Forest area aggregated at the European level for the different species

Species	Forest area (Mha)	Forest area (%)
Spruce	34.7	22
Scots Pine	48.3	30
Beech	11.7	7
Oak	11.0	7
Total	105.7	66
Others species	54.2	34

Forest age

To determine the age-class distribution of existing forests on each pixel, we used a European dataset of Pucher et al. (2022) derived from multiple national forest inventories. The dataset defines the following eight age classes: 0-20, 20-40, 40-60, 60-80, 80-100, 100-120, 120-140, and >140 years. Using this dataset, we assigned a starting value to $S_{a,t=0,s,p}$ for each age class a. To obtain 10-year age classes, we disaggregated the 20-year classes provided by Pucher et al. (2022). For each 20-year class $a = [c; d]$, 25% of the value was allocated to the lower bound c, 50% to the central year class $\frac{c+d}{2}$, and the remaining 25% to the upper bound d.

Productivity classes and growing stock volume

Forest growth was simulated based on soil- and climate-sensitive Net Primary Productivity (NPP) estimates for each tree species, derived from a deep neural network trained on simulations of a process-based forest growth model (Mohr et al., 2025). NPP is the rate at which plants and other primary producers convert solar energy into organic compounds through photosynthesis, minus the rate at which they consume these

[4] ICP is the Inline Certification Program presented here.

compounds through respiration. These NPP estimates indicate potential carbon accumulation under local conditions but do not directly provide forest growth estimates for economic modelling purposes. The NPP was simulated 500 times with historical climates using three different climate models allowing to estimate standard deviations of the estimated values.

To address this limitation, traditional yield tables were employed, which estimate the growth and dynamics of forest stand relative to its productivity level. For each species, we used yield tables encompassing a wide productivity gradient to capture the diversity of European forests. Each yield class of each species leads to a given volume, price, and rotation period. To link NPP to yield class estimates, we assume that the lowest yield class corresponds to the first percentile of the NPP distribution, while the highest yield class corresponds to the last percentile. In between, yield classes are extrapolated from NPP estimates using a linear function, based on the assumption that higher NPP corresponds to proportionally greater growth.

Economic data

Timber price

We used the values recommended by Hanewinkel et al. (2013) in their pan-European study to calculate net timber prices, commonly referred to as stumpage prices, i.e. harvest costs have been subtracted. These prices depend on the tree species and diameter. To simplify the calculations, prices were linearised across all diameters. Diameter estimates for each species were derived from yield tables and depend on the productivity class of each pixel. The prices corresponding to diameter classes are summarised in Table 7. The costs of stand established are 500 euros/ha for beech and oak, and 1,500 euros/ha and 2,000 euros/ha for pine and spruce, respectively.

Table 7: Price ($€/m^3$) of timber for different diameters

	Price ($€/m^3$)			
DBH (cm)	**Beech**	**Spruce**	**Pine**	**Oak**
5-15	0	0	0	0
15-25	5	5	5	5
25-35	10	25	20	15
35-45	25	40	35	25
45-55	40	45	40	40
> 55	50	45	45	60

Note: DBH means Diameter at Breast Height

Discount rate

The long time horizon of forest investment, with rotations exceeding 100 years, makes discounting a key factor in forest economic analysis. Following (Mohr et al., 2025), we chose a discount rate of 1.5% and simulated with a time horizon of 500 years. This closely approximates an infinite time horizon, as the economic outcome after 500 years will have negligible effects on the results.

Rotation period

We assumed that forest stands are managed according to the optimal rotation period that maximises their estimated net present value, starting from bare land and assuming infinite rotations. The optimal rotation period was calculated for each species and yield class. Table 8 shows that the estimated rotation period for each species is more than twice its mean age, suggesting that a substantial proportion of European forests has yet to reach equilibrium age (Senf, Sebald, and Seidl, 2021). The rotation period was estimated from historical climate data, weighted by the species' area on each pixel. Similarly, the double of the mean age was weighted by the species' area on each pixel.

Table 8: Comparison of rotation period and the double of mean age

	Beech	Spruce	Pine	Oak	
Rotation period (years)	130	134	170	127	
Double of mean age (years)	115	122	109	104	

In summary, we integrated four forest species (spruce, pine, beech, and oak), multiple yield classes, and a historical climate scenario into the forest age matrix-based allocation model.

Future scenarios of opportunity costs

Decisions about nature conservation, including rewilding, typically involve very long time horizons, often spanning a century. It is therefore essential to account for future opportunity costs and how these may evolve over time as a result of climate change and its impacts on crop productivity, as well as broader socio-economic developments.

Within the wildE project, we estimate opportunity costs under alternative climate-dependent crop productivity scenarios. Our approach for modelling opportunity costs on the European scale allow that opportunity costs can be modelled spatially as a function of crop productivity. Therefore, it will be possible to incorporate scenarios of changing productivity and to estimate the resulting changes in opportunity costs. In addition, relative input and output price indices may be adjusted based on assumptions derived from socio-economic scenarios. While changes in relative prices may significantly affect the overall level of opportunity costs, they are likely to be more speculative and to have a more limited influence on their spatial variation.

The proposed framework will be used to assess scenario-based opportunity costs through integrated scenario modelling, drawing on the CRAFTY modelling approach (Murray-Rust et al., 2014). To ensure internal consistency, the framework will be based on a common set of productivity scenarios across all analyses.

4. Results

Farmland value added estimates

In this section, we present and discuss the findings from the two separate econometric models, which estimate the relationship between farmland value added (VA) and key explanatory variables using the correlated random effects (CRE) framework. The first approach regresses VA on input and output prices, soil fertility, and climate conditions, while the second approach incorporates input and output prices alongside crop productivity as explanatory variables. All variables in both models behaved well and produced robust and consistent results.

France-level models – the first approach

The coefficient of input prices is statistically significant and negative, indicating that higher input costs (e.g., fertilizers, seeds, energy) reduce the farm value added (Table 9). This result aligns with economic theory, as higher input expenses reduce farm profitability, diminishing the net economic contribution from agricultural activities. Output prices show a positive and significant impact on VA, suggesting that higher prices for agricultural products (e.g., crops, livestock) lead to an increase in the farm's value added. This result underscores the importance of favorable market conditions for enhancing farm profitability.

The climate variables exhibit a non-linear impact on VA. The first-order terms for both variables are positive, meaning that moderate increases in temperature and precipitation initially boost farm performance by creating favorable growing conditions. However, the second-order terms are negative, indicating that excessive temperature or rainfall can become detrimental to farm VA. This finding is consistent with agronomic principles, where optimal weather conditions support crop growth, but extreme deviations (e.g., drought or excessive rainfall) harm agricultural output.

The impact of soil quality on VA depends on the specific physical and chemical properties of the soil. Soil physical characteristics (Clay, Silt, Sand) negatively affect VA. Soils with higher clay or silt content may have lower permeability or drainage, which could hinder crop growth and reduce farm productivity. However, soil chemical characteristics (Nitrogen, Phosphorus, Potassium, Magnesium, C/N Ratio) have a positive and significant impact on VA, highlighting the role of fertile soils rich in essential nutrients in enhancing agricultural output (Smita Tale and Ingole, 2015; Hien, Schwartz, and Garcia, 2025). The positive coefficients suggest that higher concentrations of these nutrients increase soil fertility, which translates into better crop yields and higher VA. We tested for multicollinearity and found no evidence of significant collinearity among the soil characteristics.

Table 9: Regression results of farmland value added (obs.: 19,745; number of farms: 3,236)

VARIABLES	VA		VAst		VAcap		VAlab	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Input_Price	-17.780***	1.368	-25.327***	1.426	-24.441***	1.443	-24.485***	1.352
Cereal_Price	10.264***	0.467	12.475***	0.487	12.547***	0.493	12.478***	0.462
Rainfall	237.519***	39.886	192.660***	41.574	207.192***	42.091	162.431***	39.426
Temperature	234.632***	53.081	200.467***	55.327	241.226***	56.016	179.445***	52.469
RainfallÂ^2	-161.375***	18.234	-147.122***	19.006	-150.752***	19.242	-132.205***	18.024
TemperatureÂ^2	-21.296***	4.236	-19.640***	4.416	-21.836***	4.471	-16.908***	4.188
Clay	-2.796***	0.517	-2.780***	0.523	-2.142***	0.413	-1.195***	0.218
Silt	-1.917***	0.566	-1.876***	0.574	-1.202***	0.453	-0.211	0.240
Sand	-1.340***	0.507	-1.262**	0.514	-0.877**	0.406	-0.405*	0.214
Nitrogen	110.489**	51.449	107.835**	52.092	77.974*	41.136	40.548*	21.728
Phosphorus	2,741.396***	929.294	2,635.379***	940.937	1,943.269***	743.229	1,768.532***	393.133
Potassium	161.530	196.144	164.023	198.605	188.417	156.899	106.375	83.049
Magnesium	124.028***	42.008	121.798***	42.538	79.928**	33.627	36.150**	17.856
C_N	18.222	12.602	19.300	12.760	15.068	10.085	6.264	5.350
$\overline{\text{Input Price}}$	-6.518	15.098	-10.017	15.294	-11.818	12.138	-0.260	6.588
$\overline{\text{Cereal Price}}$	2.478	6.155	4.096	6.235	4.138	4.945	-2.389	2.673
$\overline{\text{Rainfall}}$	-1,141.264**	579.976	-1,233.256**	587.486	-1,103.424**	466.226	-1,192.937***	252.760
$\overline{\text{Temperature}}$	-3,085.826***	533.867	-3,003.688***	540.875	-2,409.431***	430.068	-1,230.566***	235.284
$\overline{\text{Rainfall}^2}$	532.349**	264.183	599.598**	267.585	512.073**	212.183	524.660***	114.582
$\overline{\text{Temperature}^2}$	250.645***	40.756	245.596***	41.293	196.965***	32.847	100.540***	18.007
Constant	20,964.902***	3,441.316	21,693.397***	3,485.409	17,222.876***	2,761.738	9,796.342***	1,484.094

We have also used the cumulative temperature and rainfall over the growing period and have come up with the same results.

European-level models - Second approach

Similar to the first approach, input prices have a negative impact on farm VA (Table 10, Table 11 et Table 12). This again confirms that rising input costs reduce farm profitability and diminish the economic value added. Output prices maintain their positive effect on VA, reinforcing the conclusion that higher market prices for agricultural goods lead to increased profitability and economic performance on farms.

Crop (wheat and barley) productivity has a positive and significant effect on farm VA. This result emphasizes the direct link between higher yields and increased farm value added. The importance of productivity in driving farm VA highlights the need for sustainable agricultural practices that maintain or improve yield levels over time.

Table 10: Regression results of wheat

VARIABLES	VA		VAst		VAcap		VAlab	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Wheat productivity	34.854***	2.935	34.535***	3.377	31.652***	3.245	28.194***	2.855
Input price	-3.418***	0.772	-4.315***	0.894	-4.398***	0.869	-4.307***	0.798
Output price	3.035***	0.370	3.279***	0.428	3.105***	0.416	3.280***	0.382
Constant	1,091.179***	90.385	1,386.009***	101.503	955.456***	93.143	711.760***	71.059
Farm fixed effects	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	410,703		410,703		410,703		410,703	
Number of farms	93,202		93,202		93,202		93,202	

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Regression results of barley

VARIABLES	VA		VAst		VAcap		VAlab	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Barley productivity	41.141***	3.286	44.937***	4.013	41.498***	3.877	38.969***	3.632
Input price	-3.884***	0.733	-5.463***	0.895	-5.746***	0.864	-5.405***	0.807
Output price	2.720***	0.352	3.127***	0.430	3.150***	0.415	3.403***	0.388
Constant	871.231***	68.105	1,172.055***	79.326	782.769***	66.940	626.868***	46.571
Farm fixed effects	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	313,869		313,869		313,869		313,869	
Number of farms	75,676		75,676		75,676		75,676	

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Regression results of wheat and barley

VARIABLES	VA		VAst		VAcap		VAlab	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Wheat productivity	37.361***	1.218	38.621***	1.260	36.436***	1.228	34.886***	1.168
Barley productivity	28.227***	1.247	29.530***	1.291	27.731***	1.259	26.424***	1.202
Input price	-5.517***	0.266	-6.596***	0.275	-7.031***	0.268	-6.860***	0.256
Output price	4.233***	0.127	4.526***	0.131	4.627***	0.128	4.791***	0.122
Constant	807.839***	20.192	1,098.117***	20.678	727.856***	18.907	593.955***	15.726
Farm fixed effects	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	235,554		235,554		235,554		235,554	
Number of farms	59,240		59,240		59,240		59,240	

*** p<0.01, ** p<0.05, * p<0.1

Farmland opportunity cost predictions

France-level predictions - First approach

The predicted VA estimates provide insights into the spatial heterogeneity of agricultural profitability across France. To estimate the predicted opportunity costs of farmland, we used climate data and input/output price indices from 2010 to 2022 for each farmland plot, applying the estimated coefficients presented in Table 9. The results, summarized in Table 13, highlight notable heterogeneity across different VA calculation methods, reflecting different economic perspectives on farm profitability. The spatial unit of analysis is the municipality area containing arable land and specific climate conditions. This means that a municipality with continuous arable land but multiple climate condition grids will have multiple observations, corresponding to the number of distinct climate condition grids.

Table 13: Descriptive statistics of predicted rewilding opportunity costs, France (N= 1,375,946)

Variable	Unit	Mean	Std. Dev.	Min	Max
PGVA	€/ha	860.991	479.921	-832.927	11123.313
PVAst	€/ha	1146.111	484.375	-462.429	11109.4
PVAic	€/ha	790.743	385.773	-712.295	8688.715
PVAil	€/ha	592.639	265.652	-624.462	4787.651

PGVA (Predicted Value Added) represents the baseline measure of predicted VA, considering agricultural production and intermediate inputs. The mean PVA across all agricultural areas is €860.99/ha, with a high standard deviation (€479.92/ha) and a significant range from negative (-€832.93/ha) to highly positive (€11,123.31/ha). This suggests strong regional disparities in farm performance, possibly influenced by soil fertility, climatic conditions, and market access (Figure 1a). By including subsidies and deducting taxes, the PVAst (Predicted Value Added with Social Transfers) shows a higher mean (€1146.11/ha) and reduces the extent of negative values. The minimum value is -€462.43/ha, indicating that subsidies help mitigate financial losses in less profitable regions. The standard deviation remains high (€484.38/ha), reflecting the variability of support schemes across different areas (Figure 1b). PVAcap (Predicted Value Added Including Capital) accounts for capital depreciation, leading to a lower mean VA (€790.74/ha). The reduction in maximum and minimum values suggests that capital-intensive farms experience a significant drop in profitability once asset depreciation is factored in. This highlights the long-term opportunity costs where infrastructure and machinery of farms are adjusted, will be lover (Figure 1c). By incorporating labor costs, the PVAlab (Predicted Value Added Including Labour) reflects the net economic surplus available after covering all production expenses. The mean VA is the lowest (€592.64/ha), with a reduced range from -€624.46/ha to €4787.65/ha. The smaller variation suggests that labor costs have a stabilizing effect on profitability, but also highlight how farm profitability diminishes once all expenses are accounted for (Figure 1d).

The predicted VA reveal a strong spatial heterogeneity across agricultural regions in France (Figure 1). Several factors can explain this variability. Regions with fertile soils and favorable climatic conditions tend to exhibit higher VA, while areas with poor soil quality or extreme weather conditions[5] (e.g., drought-prone regions) show lower VA or even negative values.

We also aggregated the predicted opportunity costs of farmland by department and region, and the maps are presented in **Error! Reference source not found.**.

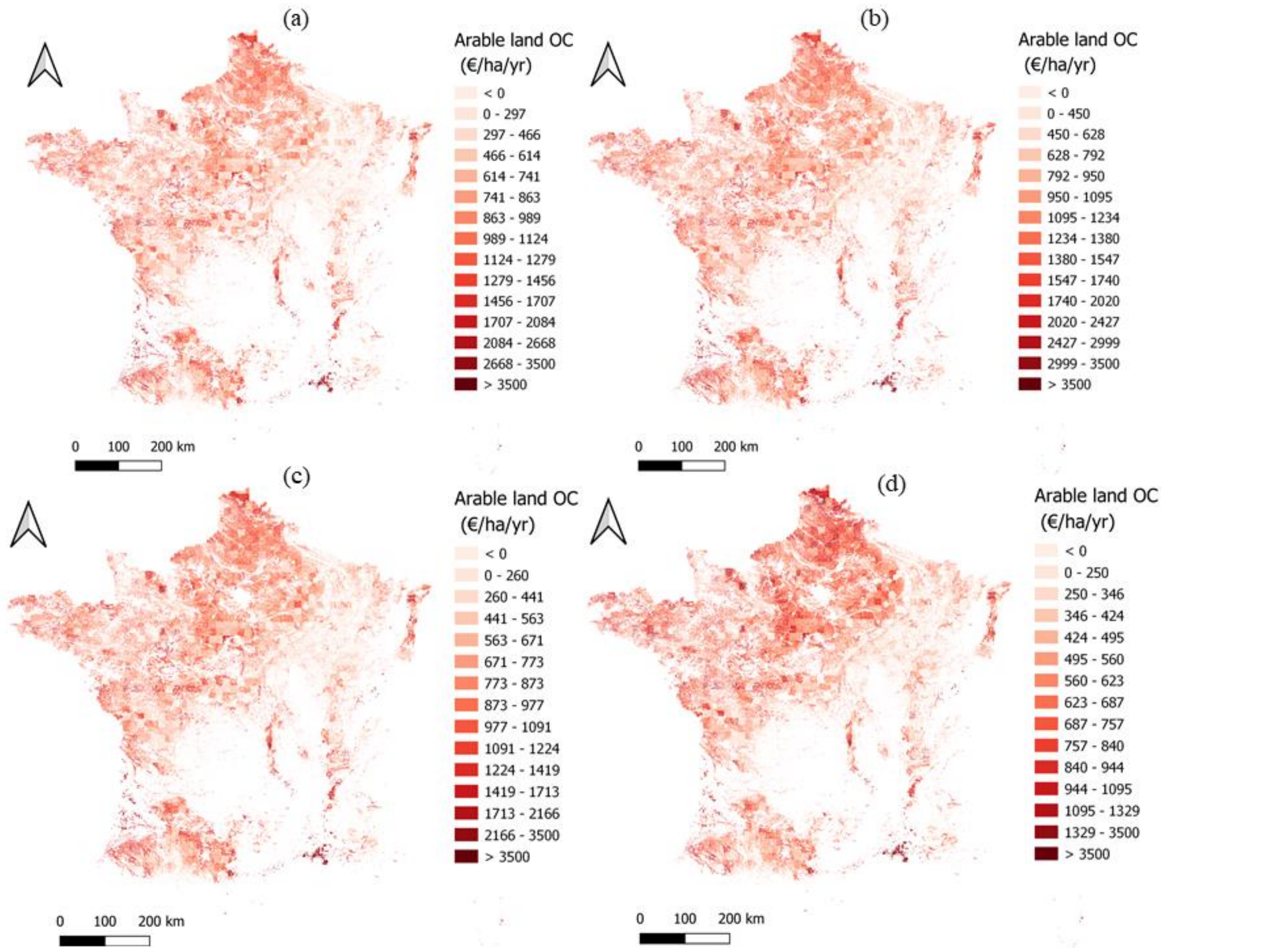

Figure 1: Opportunity costs (OC) per municipality

Note: Map (a) corresponds to the Gross Predicted Value Added (PGVA), (b) to Predicted Value Added with Social Transfers (PVAst), (c) to Predicted Value Added Including Capital (PVAcap) and (d) to Predicted Value Added Including Labour (PVAlab).

European-scale predictions - Second approach

For predicting opportunity costs, we used crop yield data from the MapSPAM v2 dataset, whereas for estimating the econometric model we used yield data from farm accounting statistics. Since we did not have access to the exact locations of farms in the farm accounting dataset, we could not use MapSPAM yields directly in the estimations. We used the input and output price indexes from 2010 for prediction as the yield data in MapSPAM corresponded to the year 2010. Table 14 summarises the predicted value-added measures

[5] It is important to note that the possibility of irrigation was not included in our model specification due to lack of detailed farm data on irrigation.

based on wheat and barley productivity across the EU. As in the French case, differences across VA metrics reflect different perspectives on farm profitability, depending on whether social transfers, capital depreciation, and labour costs are accounted for.

Table 14: Descriptive statistics of predicted opportunity costs

Variable	Obs	Mean	Std. Dev.	Min	Max
PGVA wheat		991.728	691.534	124.919	5381.966
PVAst wheat	6233	1287.905	702.217	244.927	5673.716
PVAcap wheat	5	936.414	576.323	99.609	3949.679
PVAlab wheat		775.698	484.116	36.325	3010.041
PGVA barley		830.327	633.159	28.798	5811.022
PVAst barley	6097	1094.318	650.59	107.283	6090.767
PVAcap barley	8	750.251	521.693	-33.766	4325.708
PVAlab barley		637.311	414.163	-67.659	3969.31
PGVA wheat and barley		753.417	445.933	15.273	3819.753
PVAst wheat and barley	6076	1021.796	471.896	128.718	4220.826
PVAcap wheat and barley	6	706.676	376.94	-25.548	3737.886
PVAlab wheat and barley		616.88	340.421	-75.838	3499.679

For wheat, the predicted gross value added (PGVA) is higher across all VA measures compared to barley. For example, PGVA for wheat is €991.73/ha, compared to €830.33/ha for barley. This may reflect the fact that barley is typically grown on less fertile soils and under less favourable climatic conditions than wheat. The same pattern holds for other VA measures, such as value added with social transfers (PVAst), value added including capital (PVAcap), and value added including labour (PVAlab). The combined wheat–barley VA metrics show lower mean values than the wheat-only or barley-only models. It is important to note, however, that the samples of farms used for estimation differ across the three models, as only farms producing the relevant crop are included. In addition, VA measures are only predicted for locations where the corresponding crop yield data are available in MapSPAM.

We see as in the case for France that accounting for subsidies increases the opportunity costs while accounting for capital and labour costs reduces the opportunity costs. We also see a large standard deviation of the opportunity costs indicating a strong spatial heterogeneity (see also figure 2-4). While there were some differences in estimated VA metrics depending on the yield predictor (wheat, barley, or combined) we see the same patterns with relative high values in the Benelux countries and Italy while lower values in Northern Scandinavia and the Baltic countries.

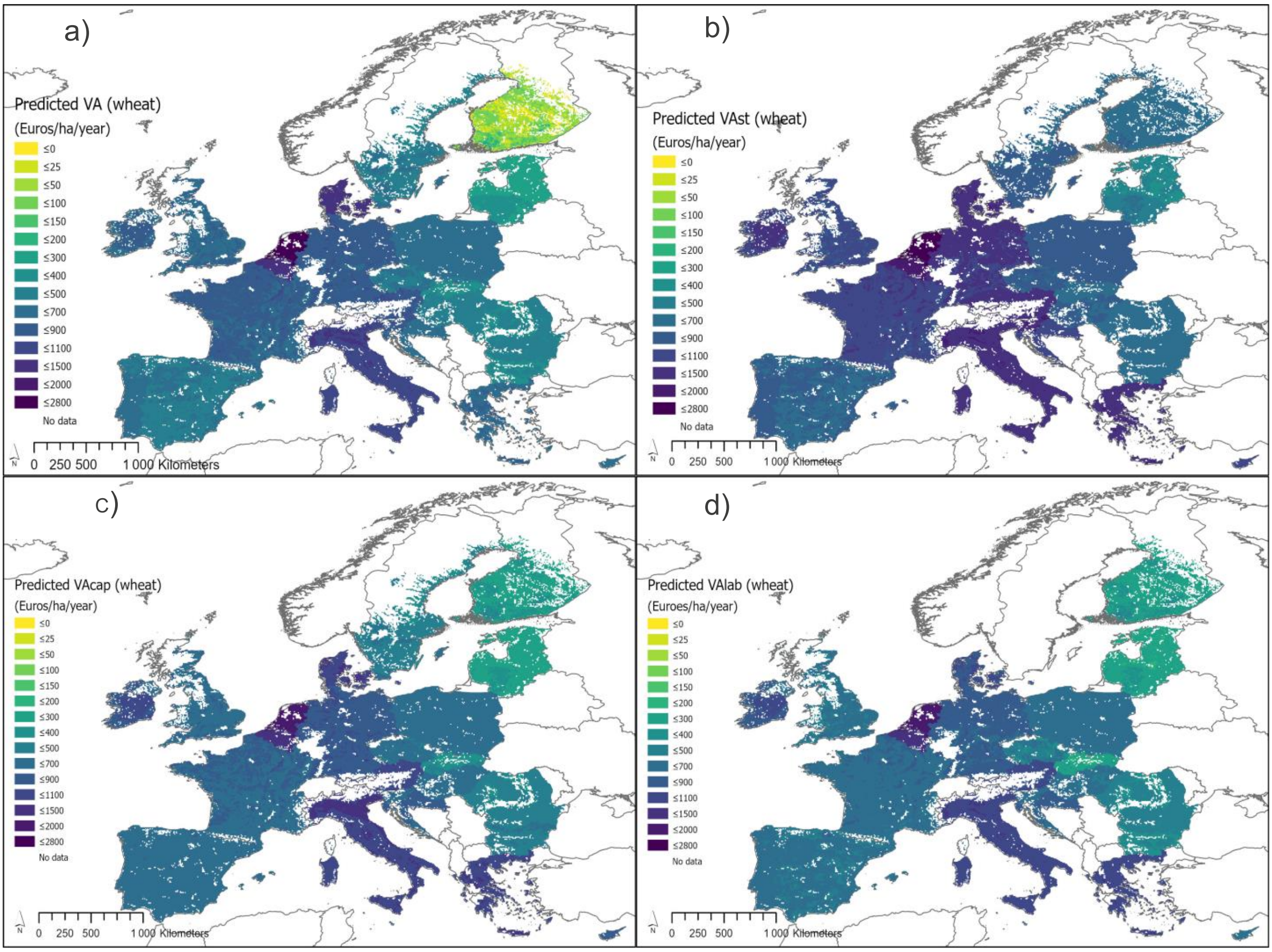

Figure 2: Farmland opportunity costs with wheat

Note: Map (a) corresponds to the Gross Predicted Opportunity Cost, (b) to Predicted Opportunity Cost with Social Transfers, (c) to Predicted Opportunity Cost Including Capital and (d) to Predicted Opportunity Cost Including Labour. White areas represent regions for which no productivity data is available.

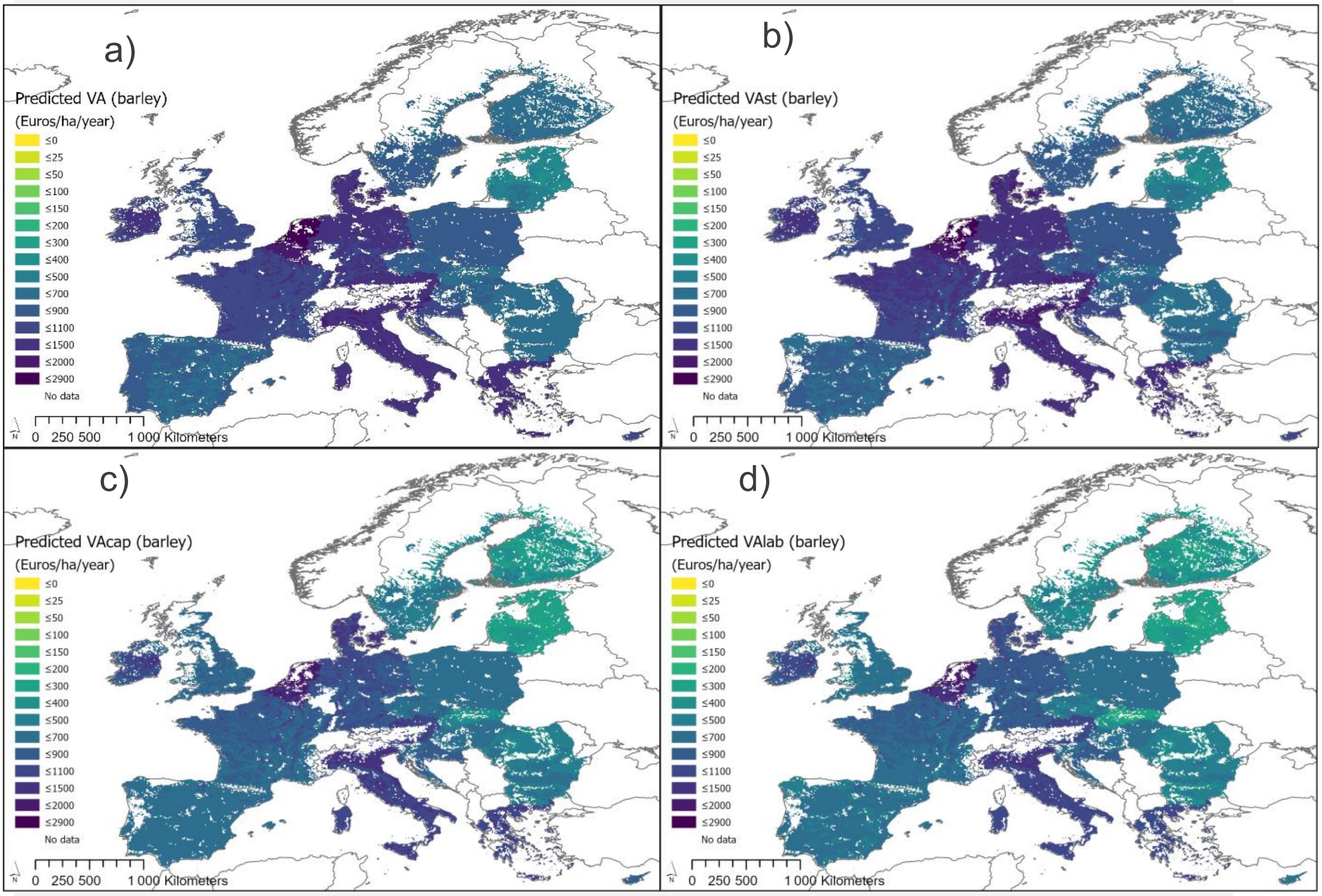

Figure 3: Farmland opportunity costs with barley

Note: Map (a) corresponds to the Gross Predicted Opportunity Cost, (b) to Predicted Opportunity Cost with Social Transfers, (c) to Predicted Opportunity Cost Including Capital and (d) to Predicted Opportunity Cost Including Labour.

The combined measure shows an increase in PVAst to €830.18/ha, but this is still below the individual crop values. The distribution of the VA is presented in Figure 4.

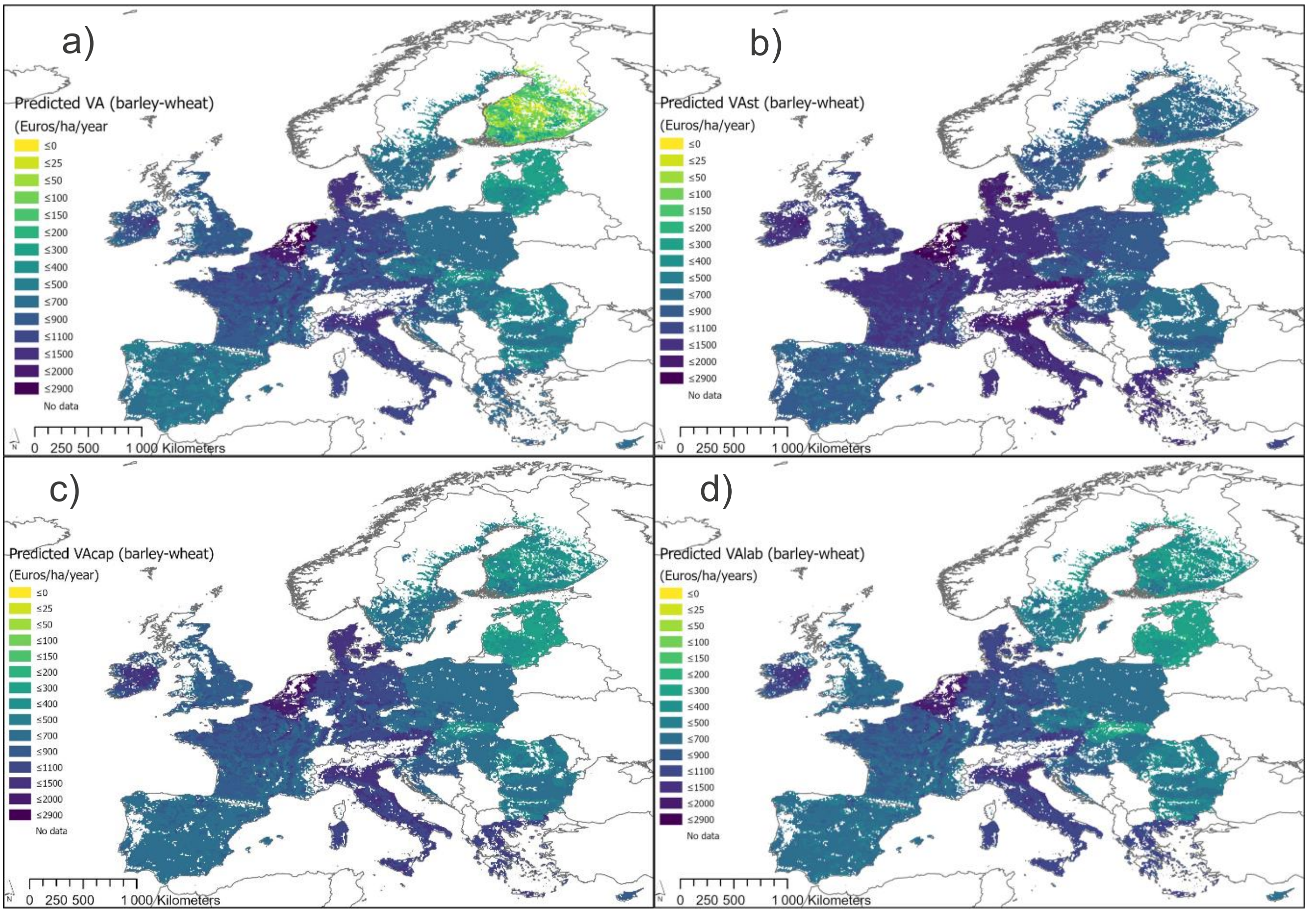

Figure 4: Farmland opportunity costs with wheat and barley

Note: Map (a) corresponds to the Gross Predicted Opportunity Cost, (b) to Predicted Opportunity Cost with Social Transfers, (c) to Predicted Opportunity Cost Including Capital and (d) to Predicted Opportunity Cost Including Labour.

Forest value added estimates

Figure 5 displays the spatial distribution of predicted opportunity costs of nature conservation for existing forest land across Europe. These values are expressed as annuities, calculated using a discount rate of 1.5% and assuming an infinite time horizon. They therefore represent the annual loss in income from timber production if future management and harvesting were ceased. The analysis also accounts for the current value of standing timber stock. This explains why high values can occur in regions with large standing stocks (for example, southern Germany).

Opportunity costs, expressed in euros per hectare per year, range from –€4 to €491, with a mean of €58 and a median of €41. The difference between the mean and median indicates a right-skewed distribution, suggesting that while some forest areas have high potential values, the majority exhibit lower opportunity costs.

Higher opportunity costs (indicated in dark green) are concentrated in Western and Central Europe, including France, Germany, Austria, Switzerland and the Czech Republic, where forest productivity is relatively high. These areas represent locations where rewilding would involve more substantial economic trade-offs. In contrast, lighter-toned areas—particularly in parts of Scandinavia, the Iberian Peninsula and Eastern Europe—show lower opportunity costs, making them more suitable for cost-effective rewilding initiatives.

Regions shown in white lack sufficient forest productivity data and were therefore excluded from the estimation. These are typically areas with minimal or no managed forest land, or areas where data coverage or quality is limited.

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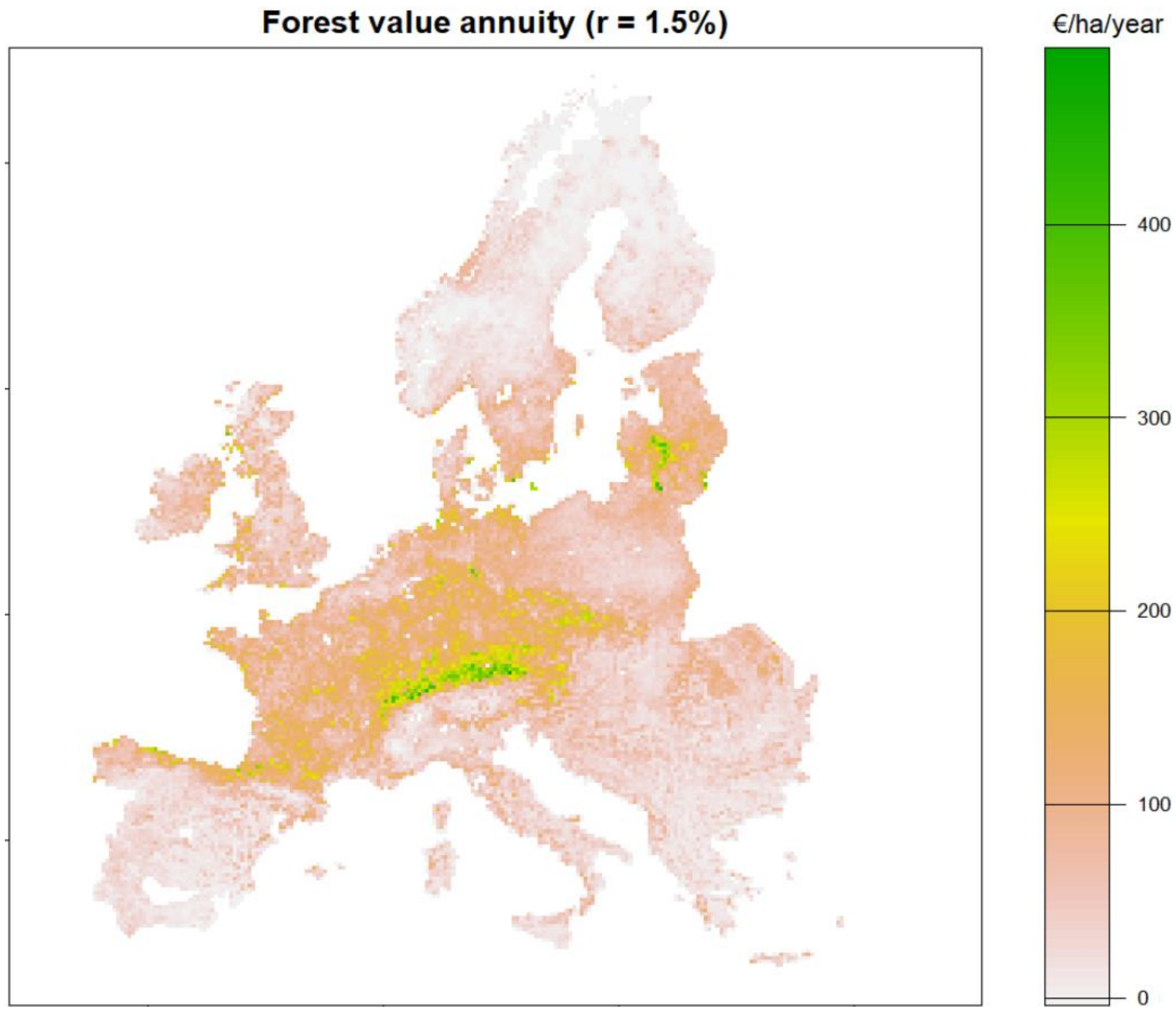


Figure 5: Forest opportunity costs (NPV in euros per ha)

Figure 6 illustrates the spatial distribution of the standard deviation of predicted forest opportunity costs for rewilding across Europe. The standard deviation is derived from simulations based on historical climate conditions. On average, the standard deviation is €11/ha/year. The largest standard deviations occur in areas where the estimated economic values are highest.

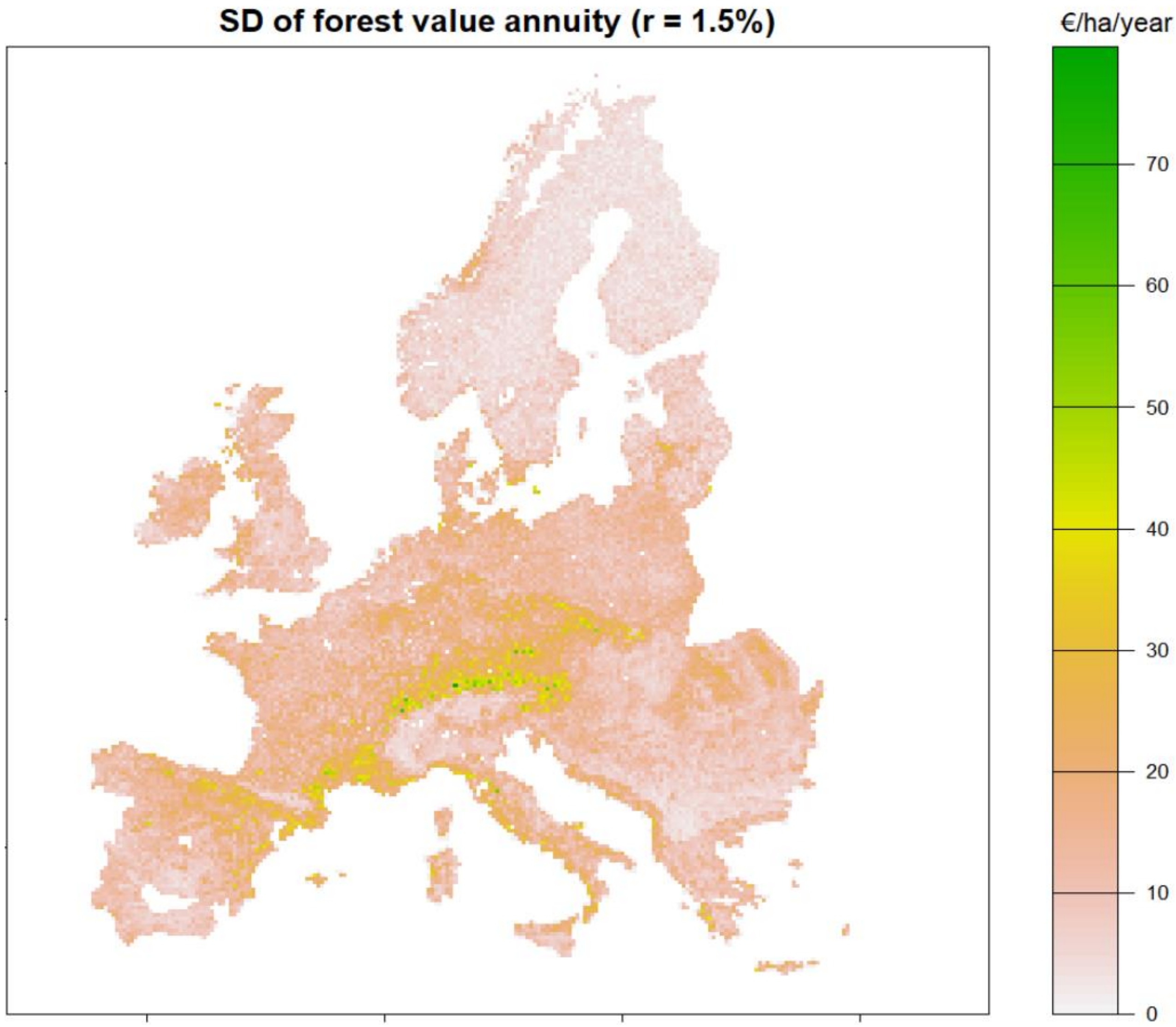


Figure 6: Standard deviation of forest opportunity costs (euros/ha/year)

5. Discussion

Comparison between the two approaches for Farmland opportunity costs

As part of the wildE project, other studies have also contributed to the identification of suitable areas for rewilding in Europe. These include the development of maps of agricultural land abandonment and de-intensification trajectories in semi-natural areas across Europe (D1.1), as well as the development of a suitability map for rewilding based on a multicriteria assessment (Kloibhofer et al., 2025). In this assessment, one criterion serves as a proxy for land potential, reflecting areas where societal demand for land is high and where rewilding is therefore less suitable. This criterion is closely related to an opportunity cost measure. In the following, we compare the land potential measure developed by Kloibhofer et al. (2025) with our estimated opportunity costs for agricultural land.

Furthermore, Spencer et al. (2025) recently provided a comprehensive spatial estimation of the opportunity costs of establishing green infrastructure in Europe, considering cropland, grassland, forest land and urban areas. We compare their opportunity cost estimates for cropland and forest land with the opportunity costs estimated in this study for farmland and forest land, respectively.

Comparing “first approach” and “second approach” for farmland opportunity costs

We estimated, for France, four measures of opportunity costs using two approaches that differ with respect to the predictor variables. Under the “first approach”, which uses soil and climate variables to capture the influence of crop productivity, we obtain opportunity cost estimates at a much finer spatial resolution than the European-scale map produced under the “second approach”.

For comparison, we resampled the outputs from the first approach to match the European grid resolution and computed the average value added (VA) within each grid cell. When comparing the two resulting maps, we observe some common patterns, such as high values in northern France, but also substantial differences (Figure 7). Correlation analysis between the two measures indicates a weak correspondence (Spearman correlation: 0.10; Pearson correlation: 0.06). We are not able to determine which approach provides the most accurate estimates.

When averaging over the European grid, we find a substantial within-cell standard deviation (195 EUR/ha/year) for PGVA, indicating high local variability in opportunity costs.

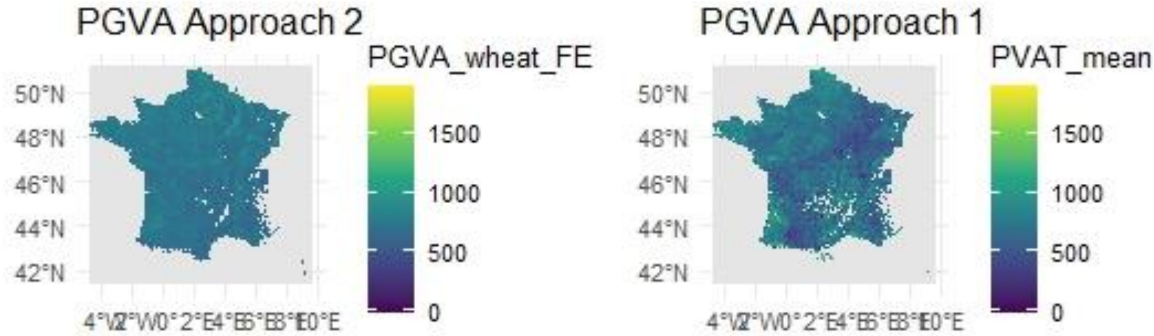


Figure 7: Comparing estimation approaches for farm land

Note: Opportunity cost (Gross Value Added) maps for France using the “first approach”, using soil and climate variables as predictors (right map) and the “second approach”, using wheat productivity as predictor (left map).

Comparison with other studies

We first compared our opportunity cost estimates with the land potential map developed in wildE for the multi-criteria analysis of rewilding suitability (Kloibhofer et al., 2025). Land potential is only one of three criteria in that analysis; the other two are ecological potential and carbon potential. Land potential consists of three sub-criteria: productivity, land abandonment, and cultural landscapes.

Because productivity is used as an input to the land potential indicator, some correspondence with our opportunity cost estimates is expected, as our approach also relies on productivity measures. In addition, the land potential indicator includes abandoned land, which can be interpreted as an economic signal that the opportunity cost of agricultural land use is low or non-positive. By contrast, the inclusion of cultural landscapes (i.e. agricultural landscapes considered worth maintaining for cultural reasons) reduces the expected link with opportunity cost measures.

Correlation analysis between the land potential indicator (normalised to a 0–1 scale) and a similarly normalised opportunity cost indicator shows, as expected, a negative relationship (Spearman: −0.26; Pearson: −0.21). This indicates that areas with high land potential for rewilding tend to coincide with areas of low opportunity costs.

When comparing the maps of opportunity costs and land potential (Figure 8), we observe relatively low opportunity costs in northern Scandinavia and on the Iberian Peninsula, where land potential for rewilding is also relatively high.

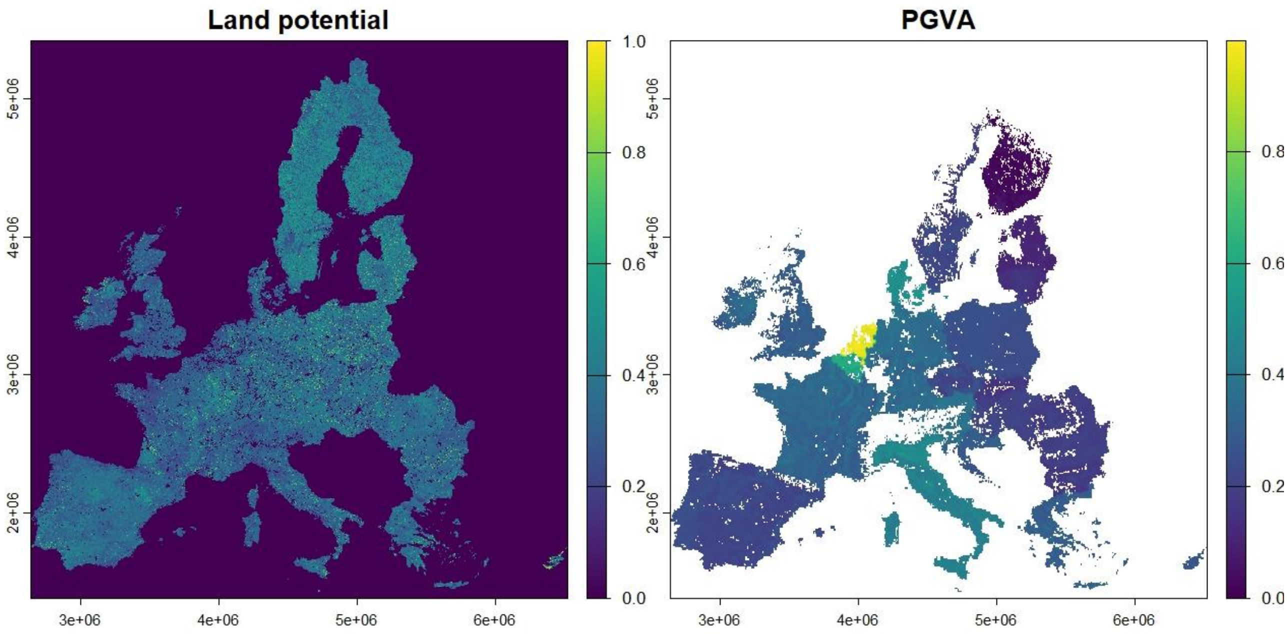


Figure 8: Comparison with land potential map from (Kloibhofer et al., 2025)

Note: Land potential map from (Kloibhofer et al., 2025) (left map) and the opportunity cost map (right map)

We also compared our cropland opportunity cost estimates with those reported in Spencer et al. (2025), which similarly use crop productivity as a spatial predictor but base the economic valuation on national agricultural land rental values. We find a relatively strong correspondence between the two datasets, with high values observed in the Benelux countries, Italy, and Denmark (Figure 9), and a correlation of approximately 0.50 across our different opportunity cost measures (Table 15).

However, the Spencer et al. (2025) dataset exhibits greater overall variation in values. This is case even after we for the comparison have aggregated values from the Spencer et al. (2025) to obtain same resolution of the two maps.

Table 15: Correlation between Spencer et al (2025) opportunity costs and different measures of opportunity cost in the present study and different predictor variable used.

Predictor variable	Pearson PGVA	Pearson PVAst	Pearson PVAcap	Pearson PVAlab	Spearman PGVA	Spearman PVAst	Spearman PVAcap	Spearman PVAlab
Wheat	0.51	0.56	0.59	0.36	0.50	0.56	0.56	0.55
Barley	0.49	0.54	0.58	0.57	0.49	0.55	0.56	0.56
Wheat–Barley	0.48	0.53	0.56	0.56	0.49	0.56	0.57	0.57

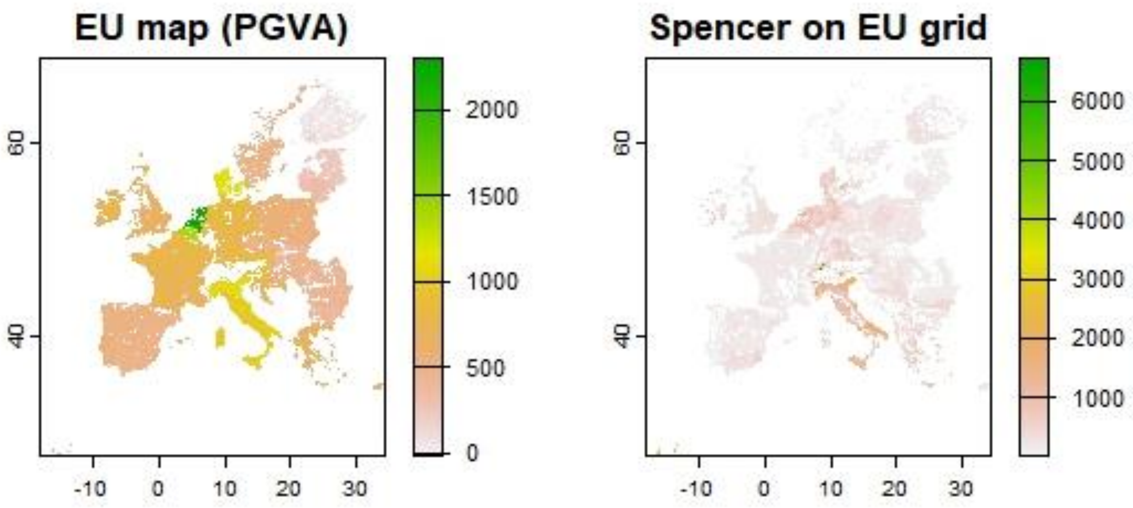


Figure 9: Comparison with cropland opportunity costs in Spencer et al (2025).

Note: The European scale map of opportunity costs (PGVA) (left map) with the cropland opportunity costs estimated by Spencer et al (2025) (right map).

Forest land opportunity cost comparisons

For comparison, we benchmarked our forest land opportunity cost estimates against those provided by Spencer et al. (2025). We first aggregated the Spencer dataset to match the spatial resolution of our 16 × 16 km grid. Despite the methodological differences between the two approaches, the estimates are of a similar magnitude: mean values differ by only about €5/ha/year (Table 1Table 16). The spatial correlation between the two datasets is moderate, with Pearson and Spearman correlation coefficients of 0.42 and 0.48, respectively.

Spencer et al. (2025) estimate forest opportunity costs by combining gridded woody biomass yield data from the wood production dataset of Verkerk et al. (2015) with national timber prices. These spatial timber value estimates are then used to allocate national forest rent estimates across grid cells. This approach does not account for the current age structure of forest stands and therefore ignores variation in standing timber volume. In contrast, our approach incorporates the current standing timber stock through stand age, which can lead to higher opportunity costs in areas with large standing volumes, as stopping exploitation implies an immediate loss of harvest value.

Figure 10 compares the two maps and shows broadly consistent spatial patterns, with higher opportunity costs concentrated in Central Europe. Figure 11 further presents the difference between the two datasets, calculated as Spencer et al. (2025) minus our estimates. Red values indicate areas where our opportunity costs are lower than those reported by Spencer et al. (2025), whereas blue values indicate areas where our estimates are higher.

It is not possible to determine which dataset provides the most accurate estimates, as both rely on different assumptions and data sources.

The difference map suggests that our approach underestimates opportunity costs in south-western France (Landes), where maritime pine (*Pinus pinaster*) dominates and is a species not explicitly represented in our modelling framework. In addition, we observe higher opportunity costs in southern Germany and parts of northern Austria and Switzerland. This may partly reflect older forest stands with higher standing volumes, for which taking land out of production implies a larger immediate loss of harvest value.

Table 16: Summary statistics of forest opportunity costs (€/ha/year)

Measure	Min	Max	Mean	Median
This study	–3.82	491.32	57.87	41.46
Spencer et al. 2025 (16 x 16 km)	0.00	595.54	52.61	38.91

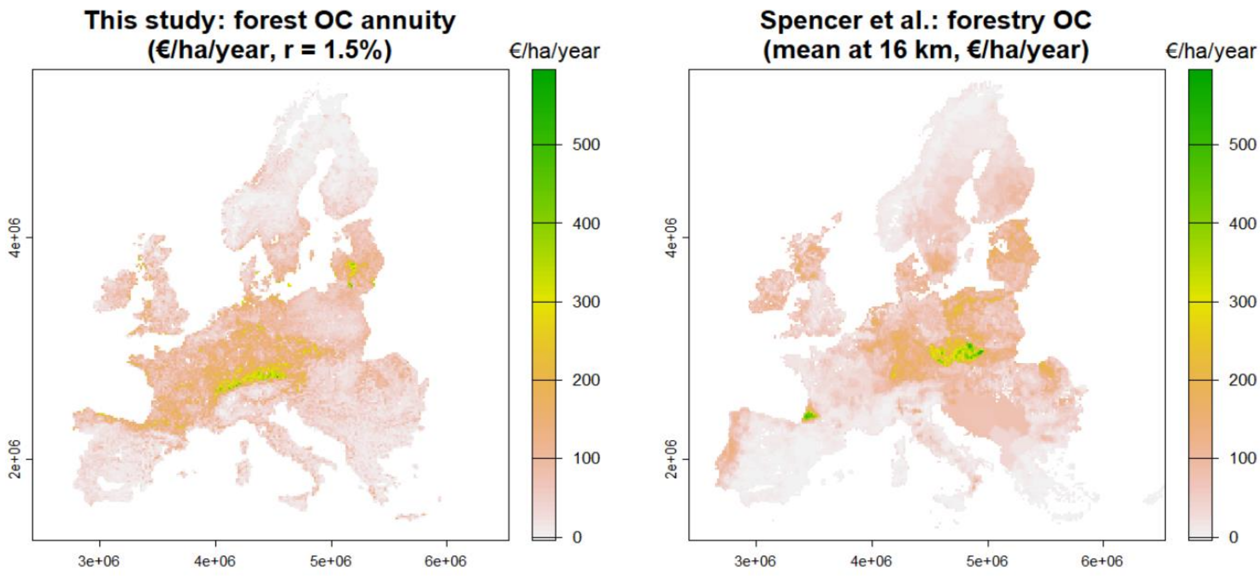


Figure 10: Comparison with forest land opportunity costs in Spencer et al (2025).

Note: Annual opportunity estimated for Europe based on the present study (left map) and Spencer et al (2025) (right map).

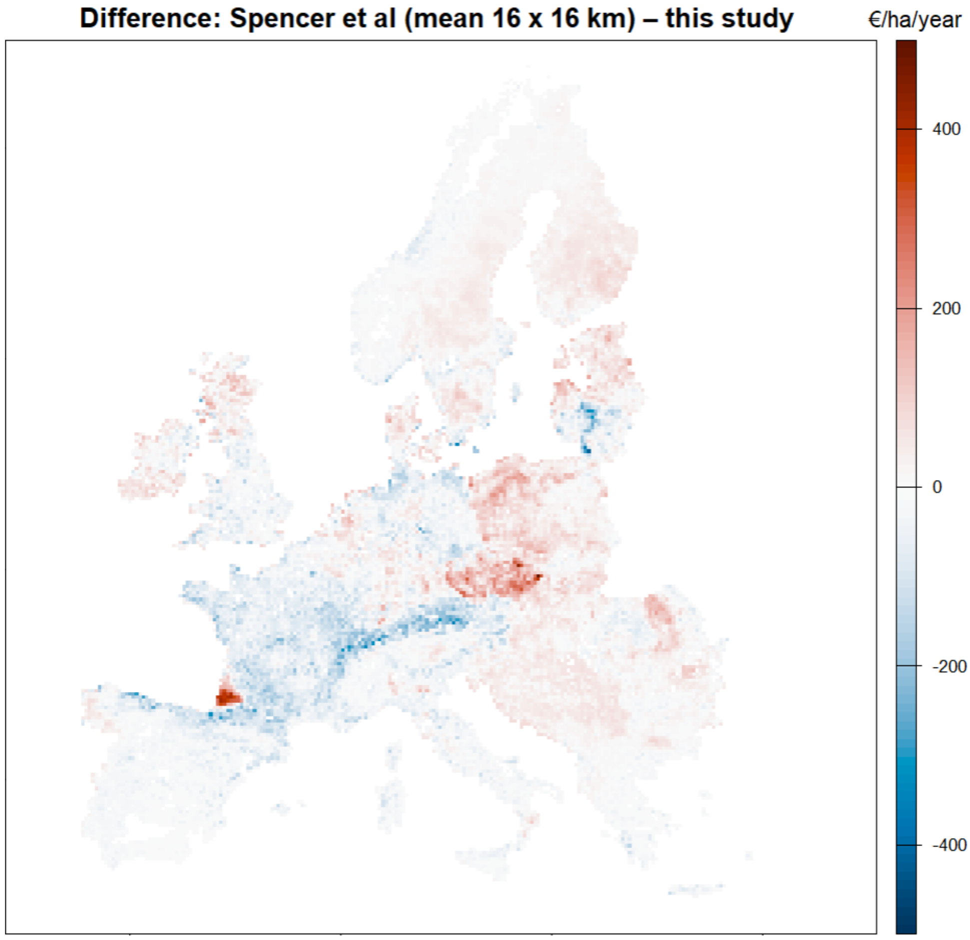


Figure 11: Differences between opportunity cost estimates in Spencer et al. (2015) and our estimates

Limits and research perspectives

We estimated a spatially explicit opportunity cost map for nature conservation on farmland in EU countries based on crop productivity and price indices. Our model is calibrated using a farm accounting dataset that allows for the estimation of different measures of opportunity costs corresponding to alternative analytical objectives (financial versus economic analysis) and contexts (e.g. inclusion of the opportunity costs of capital and labour). This represents a major advancement compared to other comprehensive studies (e.g. Spencer et al., 2025). Their approach relies on land rent as a proxy for opportunity costs, which can be considered theoretically appropriate provided that rental land markets are efficient and that potential amenity values affecting land rents would also be lost under conservation. Furthermore, observed rental prices may depend on the extent to which subsidies are captured by tenants or landowners. In this respect, our study is more transparent regarding the underlying assumptions and the definition of opportunity costs.

However, we identify substantial spatial uncertainty in the estimation of opportunity costs, reflected in differences between alternative modelling approaches — whether predictions are based on climate and soil variables or on observed crop yields.

An important limitation of the present study is that grassland is not modelled explicitly, unlike in Spencer et al. (2025). Initial attempts to estimate the marginal value of grassland using farm accounting data did not produce robust results. Since wheat and/or barley productivity is used as the main predictor of opportunity costs, our results should primarily be applied to land where these crops could potentially be grown. This excludes certain pasture-dominated areas that are not realistically convertible to arable crop production, for example in mountainous regions.

Another important assumption of our model is that livestock production is treated as largely decoupled from land use. This assumption may not always hold, particularly in systems where land availability constrains manure spreading and compliance with nutrient regulations.

Regarding forest opportunity costs, the model is simplified by considering only the four most common tree species. In some regions, this leads to lower reliability where forest composition is not adequately represented by these species. Future extensions of the forest model should incorporate climate change scenarios affecting forest growth and disturbance regimes. Including these factors would likely reduce opportunity costs in a spatially heterogeneous manner (Mohr et al., 2025).

6. Conclusion

This study presents a comprehensive and spatially explicit assessment of the opportunity costs associated with rewilding agricultural and forest land across Europe. By combining detailed farm-level economic data, crop yield maps, forest simulations, and biophysical indicators, we generate high-resolution estimates that capture both the heterogeneity and complexity of rewilding trade-offs.

Our results demonstrate substantial spatial variation in opportunity costs, driven by differences in soil fertility, climatic conditions, input and output prices, and production systems. Forested areas in Western and Central Europe — such as Switzerland, Germany, and parts of France — exhibit particularly high costs, whereas more peripheral or less productive regions in Eastern and Southern Europe present comparatively lower-cost rewilding potential. In agricultural landscapes, profitability — measured through alternative value-added indicators — declines markedly once capital and labour costs are fully accounted for, underscoring the importance of a multidimensional approach to assessing the economic implications of land-use change.

The analysis further highlights the central role of agricultural subsidies in shaping farm-level financial viability and, consequently, the estimated costs of rewilding.

By providing consistent, transparent, and policy-relevant estimates, this work supports more informed conservation planning and nature restoration strategies. It reinforces the need to align economic efficiency with ecological ambition when prioritising rewilding initiatives under the EU Biodiversity Strategy and the forthcoming Nature Restoration Law.

Finally, the framework for predicting opportunity costs as a function of crop productivity and relative prices allows the modelling of future scenarios reflecting changes in climate, technological progress, and market conditions. This forward-looking dimension strengthens its relevance for long-term policy design under uncertainty.

7. Data availability

Data used for this study.

French FADN database:

https://www.casd.eu/en/source/agricultural-accounting-information-network/

European FADN database:

https://agridata.ec.europa.eu/extensions/FarmEconomyFocus/FADNDatabase.html

Input and output price indices (2020 = 100):

https://ec.europa.eu/eurostat/web/agriculture/database

French consumer price index - Base 2015:

https://www.insee.fr/fr/statistiques/serie/001763852

European Harmonised Index of Consumer Prices (HICP):

https://ec.europa.eu/eurostat/databrowser/view/prc_hicp_aind__custom_15636115/default/table?lang=en

Corine land cover maps:

https://land.copernicus.eu/en/products/corine-land-cover/clc2018#download

French metropolitan municipalities maps:

https://geoservices.ign.fr/geofla

Soil Quality Measurement Network (RMQS):

https://entrepot.recherche.data.gouv.fr/dataset.xhtml?persistentId=doi:10.15454/QSXKGA

Soil bulk density data from the Soil Quality Measurement Network:

https://entrepot.recherche.data.gouv.fr/dataset.xhtml?persistentId=doi%3A10.57745%2FEM5IDL&version=DRAFT

LUCAS 2018 topsoil data:

https://esdac.jrc.ec.europa.eu/content/lucas-2018-topsoil-data

Crop yield data of the Spatial Production Allocation Model (MapSPAM v2 dataset):

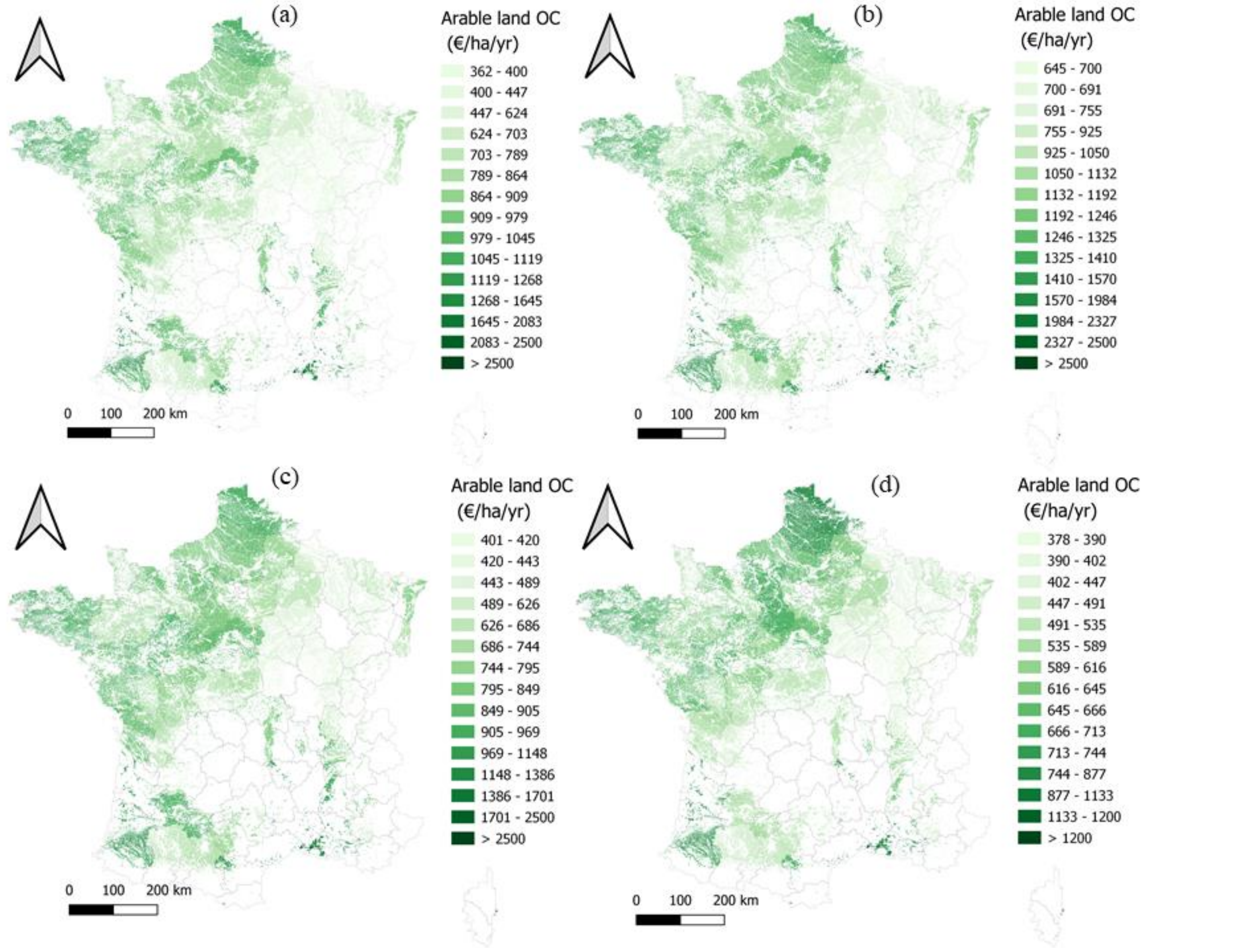
https://www.mapspam.info/data/

Maps produced in this project

The maps produced in this paper are available from the author upon request (jens.abildtrup@inrae.fr).

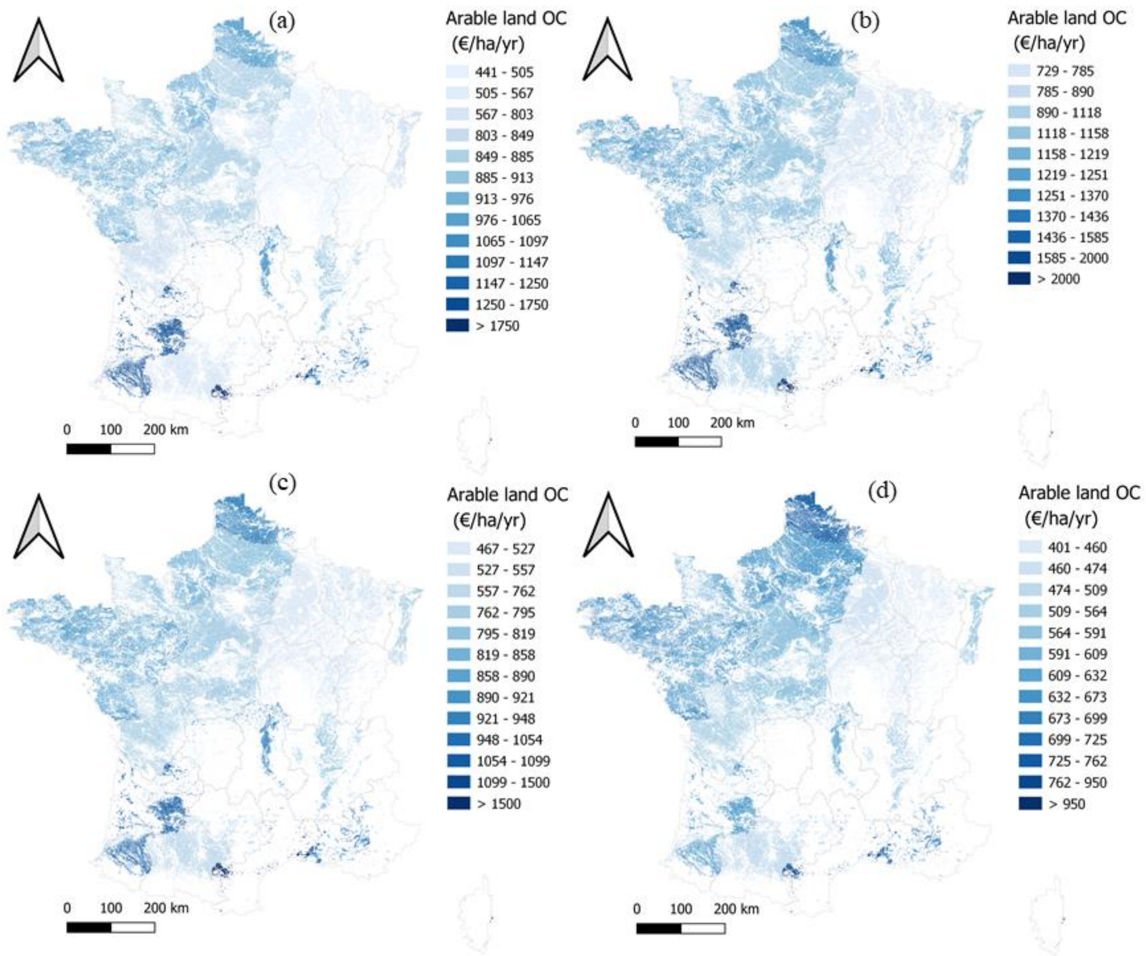
8. Appendix

Figure A 1: Opportunity costs per department in France



Note: Map (a) corresponds to the Gross Predicted Value Added, (b) to Predicted Value Added with Social Transfers, (c) to Predicted Value Added Including Capital and (d) to Predicted Value Added Including Labour.

Figure A2: Opportunity costs per region in France



Note: Map (a) corresponds to the Gross Predicted Value Added, (b) to Predicted Value Added with Social Transfers, (c) to Predicted Value Added Including Capital and (d) to Predicted Value Added Including Labour.

9. References

Adams, V.M. 2024. "Costs in Conservation: Common Costly Mistakes and How to Avoid Them." *PLoS Biology* 22(6 June). Public Library of Science. doi: 10.1371/journal.pbio.3002676.

Adams, V. M., Pressey, R. L., & Naidoo, R. 2010. Opportunity costs: Who really pays for conservation? *Biological Conservation*, *143*(2), 439–448. https://doi.org/10.1016/j.biocon.2009.11.011

Adhikari, K., and A.E. Hartemink. 2016. "Linking Soils to Ecosystem Services - A Global Review." *Geoderma* 262: 101–111. doi: 10.1016/j.geoderma.2015.08.009.

Ando, A., J. Camm, S. Polasky, and A. Solow. 1998. "Species Distributions, Land Values, and Efficient Conservation." *Science* 279(5359): 2126–2128. doi: 10.1126/science.279.5359.2126.

Armsworth, P.R. 2014. "Inclusion of Costs in Conservation Planning Depends on Limited Datasets and Hopeful Assumptions." *Annals of the New York Academy of Sciences* 1322(1): 61–76. doi: 10.1111/nyas.12455.

Armsworth, P.R., G.C. Daily, P. Kareiva, and J.N. Sanchirico. 2006. "Land Market Feedbacks Can Undermine Biodiversity Conservation." *Proceedings of the National Academy of Sciences of the United States of America* 103(14): 5403–8. doi: 10.1073/pnas.0505278103.

Bareille, F., and R. Chakir. 2024. "Structural Identification of Weather Impacts on Crop Yields: Disentangling Agronomic from Adaptation Effects." *American Journal of Agricultural Economics* 106(3). John Wiley and Sons Inc: 989–1019. doi: 10.1111/ajae.12420.

Bastit, F. 2023. "An Economic Approach to Multiple Risks in Forests."

Bateman, I.J., C. Ennew, A.A. Lovett, and A.J. Rayner. 1999. "Modelling and Mapping Agricultural Output Values Using Farm Specific Details and Environmental Databases." *Journal of Agricultural Economics* 50(3): 488–511. doi: 10.1111/j.1477-9552.1999.tb00895.x.

Bertuzzi, P., and P. Clastre. 2022. *Information sur les mailles SAFRAN*. Recherche Data Gouv. doi: doi:10.57745/1PDFNL.

Bladt, J., N. Strange, J. Abildtrup, J.C. Svenning, and F. Skov. 2009. "Conservation Efficiency of Geopolitical Coordination in the EU." *Journal for Nature Conservation* 17(2). Elsevier: 72–86. doi: 10.1016/j.jnc.2008.12.003.

Brus, D.J., G.M. Hengeveld, D.J.J. Walvoort, P.W. Goedhart, A.H. Heidema, G.J. Nabuurs, and K. Gunia. 2012. "Statistical Mapping of Tree Species over Europe." *European Journal of Forest*

Research 131(1): 145–157. doi: 10.1007/s10342-011-0513-5.

Bryan, B.A., D. King, and J.R. Ward. 2011. "Modelling and Mapping Agricultural Opportunity Costs to Guide Landscape Planning for Natural Resource Management." *Ecological Indicators* 11(1): 199–208. doi: 10.1016/j.ecolind.2009.02.005.

Carles, R. 1969. "Nouvel Instrument d'observation Pour La Statistique Agricole : Le Réseau d'information Comptable." *Economie et Statistique* 6(1): 62–66. doi: 10.3406/estat.1969.1898.

Carwardine, J., K.A. Wilson, G. Ceballos, P.R. Ehrlich, R. Naidoo, T. Iwamura, S.A. Hajkowicz, and H.P. Possingham. 2008. *Cost-Effective Priorities for Global Mammal Conservation*. Available online at www.pnas.orgcgidoi10.1073pnas.0707157105.

Ceausu, S., M. Hofmann, L.M. Navarro, S. Carver, P.H. Verburg, and H.M. Pereira. 2015. "Mapping Opportunities and Challenges for Rewilding in Europe." *Conservation Biology* 29(4): 1017–1027. doi: 10.1111/cobi.12533.

Chatellier, V., and H. Guyomard. 2023. "Supporting European Farmers' Incomes through Common Agricultural Policy Direct Aids: Facts and Questions." *Review of Agricultural, Food and Environmental Studies* 104. Springer Paris: 87–99. doi: 10.1007/s41130-023-00192-8.

Costello, C., and S. Polasky. 2004. "Dynamic Reserve Site Selection." *Resource and Energy Economics* 26(2): 157–174. doi: 10.1016/j.reseneeco.2003.11.005.

Cunningham, C.A., H.Q.P. Crick, M.D. Morecroft, C.D. Thomas, and C.M. Beale. 2021. "Translating Area-Based Conservation Pledges into Efficient Biodiversity Protection Outcomes." *Communications Biology* 4(1). Springer US: 1–5. doi: 10.1038/s42003-021-02590-4.

Doelman, J.C., E. Stehfest, D.P. van Vuuren, A. Tabeau, A.F. Hof, M.C. Braakhekke, D.E.H.J. Gernaat, M. van den Berg, W.J. van Zeist, V. Daioglou, H. van Meijl, and P.L. Lucas. 2020. "Afforestation for Climate Change Mitigation: Potentials, Risks and Trade-Offs." *Global Change Biology* 26(3): 1576–1591. doi: 10.1111/gcb.14887.

Fastré, C., W.J. van Zeist, J.E.M. Watson, and P. Visconti. 2021. "Integrated Spatial Planning for Biodiversity Conservation and Food Production." *One Earth* 4(11): 1635–1644. doi: 10.1016/j.oneear.2021.10.014.

Faure, E., H. Levrel, and F. Quétier. 2024. "Economics of Rewilding." *Ambio* 53(9): 1367–1382. doi: 10.1007/s13280-024-02019-2.

FOREST EUROPE. 2020. *State of Europe's Forests 2020. Technical Report.*

Gollier, C., P. Koundouri, and T. Pantelidis. 2008. "Declining Discount Rates: Economic

Justifications and Implications for Long-Run Policy." *Economic Policy* 23(56): 757–795.

Golub, A., T. Hertel, H.L. Lee, S. Rose, and B. Sohngen. 2009. "The Opportunity Cost of Land Use and the Global Potential for Greenhouse Gas Mitigation in Agriculture and Forestry." *Resource and Energy Economics* 31(4): 299–319. doi: 10.1016/j.reseneeco.2009.04.007.

Goodwin, B.K., A.K. Mishra, and F.N. Ortalo-Magné. 2003. *What's Wrong with Our Models of Agricultural Land Values? American Journal of Agricultural Economics*.

Granado-Díaz, R., A.J. Villanueva, and J.A. Gómez-Limón. 2022. "Willingness to Accept for Rewilding Farmland in Environmentally Sensitive Areas." *Land Use Policy* 116. doi: 10.1016/j.landusepol.2022.106052.

Greiner, L., A. Keller, A. Grêt-Regamey, and A. Papritz. 2017. "Soil Function Assessment: Review of Methods for Quantifying the Contributions of Soils to Ecosystem Services." *Land Use Policy* 69. Elsevier BV: 224–237. doi: 10.1016/j.landusepol.2017.06.025.

Hanewinkel, M., D.A. Cullmann, M.J. Schelhaas, G.J. Nabuurs, and N.E. Zimmermann. 2013. "Climate Change May Cause Severe Loss in the Economic Value of European Forest Land." *Nature Climate Change* 3(3). Nature Publishing Group: 203–207. doi: 10.1038/nclimate1687.

Hien, T., C. Schwartz, and S. Garcia. 2025. "From Soil Sciences to Soil Economics: A Cross-Analysis of Natural Capital and Soil Ecosystem Service Provision." *Environmental Science & Policy* 169: 104088. doi: https://doi.org/10.1016/j.envsci.2025.104088.

Institut National de la Recherche Agronomique, Association marnaise de développement agricole et viticole, Association pour la Relance Agronomique en Alsace (ARAA), Chambre Départementale d'Agriculture des Ardennes, Chambre Départementale d'Agriculture de l'Aube, Chambre Départementale d'Agriculture du Calvados, Chambre Départementale d'Agriculture de Charente, Chambre Départementale d'Agriculture de Charente-Maritime, Chambre Départementale d'Agriculture du Cher, Chambre Départementale d'Agriculture de Corrèze, Chambre Départementale d'Agriculture de la Côte D'Or, Chambre Départementale d'Agriculture de Creuse, Chambre Départementale d'Agriculture des Deux-Sèvres, Chambre Départementale d'Agriculture de L'Eure, Chambre Départementale d'Agriculture de L'Eure-et-Loir, Chambre Départementale d'Agriculture de Haute-Marne, Chambre Départementale d'Agriculture de Haute-Vienne, Chambre Départementale d'Agriculture de L'Indre, Chambre Départementale d'Agriculture de Loire-Atlantique, and Chambre Départementale d'Agriculture de Mayenne. 2021. *Analyses physico-chimiques des sites du Réseau de Mesures de la Qualité des Sols (RMQS) du territoire métropolitain pour la 1ère campagne (2000-2009), avec* *coordonnées théoriques*. l'alimentation et l'environnement Institut national de recherche pour l'agriculture, ed. Recherche Data Gouv. doi: doi:10.15454/QSXKGA.

Jung, M., Alagador, D., Chapman, M., Hermoso, V., Kujala, H., O'Connor, L., Schinegger, R., Verburg, P. H., & Visconti, P. 2024. An assessment of the state of conservation planning in Europe. In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 379, Number 1902). Royal Society Publishing. https://doi.org/10.1098/rstb.2023.0015

Kloibhofer, J., Prestele, R., Leitinger, G., & Rounsevell, M. 2025. Where could climate-smart rewilding be located in Europe? *Journal of Environmental Management*, *380*. https://doi.org/10.1016/j.jenvman.2025.125084

Knoke, T., E. Gosling, D. Thom, C. Chreptun, A. Rammig, and R. Seidl. 2021. "Economic Losses from Natural Disturbances in Norway Spruce Forests – A Quantification Using Monte-Carlo Simulations." *Ecological Economics* 185(January). Elsevier B.V.: 107046. doi: 10.1016/j.ecolecon.2021.107046.

Lautrup, M., T.E. Panduro, J. V. Olsen, M.F. Pedersen, and J.B. Jacobsen. 2023. "Is There More to Trees than Timber? Estimating the Private Amenity Value of Forests Using a Hedonic Land Model for Combined Agricultural Properties." *Forest Policy and Economics* 146(November 2022). Elsevier B.V.: 102867. doi: 10.1016/j.forpol.2022.102867.

Lundhede, T.H., and B.J. Thorsen. 2017. *Estimating Opportunity Costs of Setting aside Forest for Biodiversity*.

Mankiw, N.G. 2016. *Principles of Microconomics*. Fourth edi. Worth Publisher.

Mewes, M., M. Drechsler, K. Johst, A. Sturm, and F. Wätzold. 2015. "A Systematic Approach for Assessing Spatially and Temporally Differentiated Opportunity Costs of Biodiversity Conservation Measures in Grasslands." *Agricultural Systems* 137. Elsevier Ltd: 76–88. doi: 10.1016/j.agsy.2015.03.010.

Mohr, J. S., Bastit, F., Grünig, M., Knoke, T., Rammer, W., Senf, C., Thom, D., & Seidl, R. 2025. Rising cost of disturbances for forestry in Europe under climate change. *Nature Climate Change*. https://doi.org/10.1038/s41558-025-02408-9

Moreno, A., M. Neumann, and H. Hasenauer. 2017. "Forest Structures across Europe." *Geoscience Data Journal* 4(1): 17–28. doi: 10.1002/gdj3.45.

Mundlak, Y. 1978. *On the Pooling of Time Series and Cross Section Data Econometrica*. doi: 10.2307/1913646.

Musumba, M., C.A. Palm, A.M. Komarek, P.K. Mutuo, and B. Kaya. 2022. "Household Livelihood Diversification in Rural Africa." *Agricultural Economics (United Kingdom)* 53(2): 246–256. doi: 10.1111/agec.12694.

Mutillod, C., E. Buisson, G. Mahy, R. Jaunatre, J.M. Bullock, L. Tatin, and T. Dutoit. 2024. "Ecological Restoration and Rewilding : Two Approaches with Complementary Goals ?" *Biological Reviews* 9: 000–000. doi: 10.1111/brv.13046.

Naidoo, R., and W.L. Adamowicz. 2006. "Modeling Opportunity Costs of Conservation in Transitional Landscapes." *Conservation Biology* 20(2): 490–500. doi: 10.1111/j.1523-1739.2006.00304.x.

Naidoo, R., and T. Iwamura. 2007. "Global-Scale Mapping of Economic Benefits from Agricultural Lands: Implications for Conservation Priorities." *Biological Conservation* 140(1–2): 40–49. doi: 10.1016/j.biocon.2007.07.025.

Naidoo, R., A. Balmford, P.J. Ferraro, S. Polasky, T.H. Ricketts, and M. Rouget. 2006. "Integrating Economic Costs into Conservation Planning." *Trends in Ecology and Evolution* 21(12): 681–687. doi: 10.1016/j.tree.2006.10.003.

Nolte, C. 2020. "High-Resolution Land Value Maps Reveal Underestimation of Conservation Costs in the United States." *Proceedings of the National Academy of Sciences of the United States of America* 117(47): 29577–29583. doi: 10.1073/pnas.2012865117.

Pereira, H.M., and L.M. Navarro. 2015. *Rewilding European Landscapes*. H.M. Pereira and L.M. Navarro, eds. New York: Springer Open. doi: 10.1007/978-3-319-12039-3_7.

Piet, L., V. Chatellier, P. Jeanneaux, C. Laroche-Dupraz, A. Ridier, and P. Veysset. 2020. *Les Indicateurs de Revenu Dans Les Exploitations Agricoles En France : Une Analyse Comparée Sur 15 Ans Entre Les Données Du RICA et Celles de La MSA*. Available online at https://www6.rennes.inrae.fr/smart/Contrats-de-recherche/Agr-Income.

Polasky, S., J.D. Camm, and B. Garber-Yonts. 2001. "Selecting Biological Reserves Cost-Effectively: An Application to Terrestrial Vertebrate Conservation in Oregon." *Land Economics* 77(1): 68–78.

Polasky, S., E. Nelson, J. Camm, B. Csuti, P. Fackler, E. Lonsdorf, C. Montgomery, D. White, J. Arthur, B. Garber-Yonts, R. Haight, J. Kagan, A. Starfield, and C. Tobalske. 2008. "Where to Put Things? Spatial Land Management to Sustain Biodiversity and Economic Returns." *Biological Conservation* 141: 1505–1524. Available online at http://www.sciencedirect.com/science/article/B6V5X-4SJR2HX-1/2/244c8497b3769ed5d5d232c404832f76.

Ragasa, C. 2020. “Effectiveness of the Lead Farmer Approach in Agricultural Extension Service Provision: Nationally Representative Panel Data Analysis in Malawi.” *Land Use Policy* 99(February 2019). Elsevier: 104966. doi: 10.1016/j.landusepol.2020.104966.

Rennert, K., F. Errickson, B.C. Prest, L. Rennels, R.G. Newell, W. Pizer, C. Kingdon, J. Wingenroth, R. Cooke, B. Parthum, D. Smith, K. Cromar, D. Diaz, F.C. Moore, U.K. Müller, R.J. Plevin, A.E. Raftery, H. Ševčíková, H. Sheets, J.H. Stock, T. Tan, M. Watson, T.E. Wong, and D. Anthoff. 2022. “Comprehensive Evidence Implies a Higher Social Cost of CO2.” *Nature* 610(7933). Springer US: 687–692. doi: 10.1038/s41586-022-05224-9.

Rodewald, A.D., M. Strimas-Mackey, R. Schuster, and P. Arcese. 2019. “Tradeoffs in the Value of Biodiversity Feature and Cost Data in Conservation Prioritization.” *Scientific Reports* 9(1): 1–8. doi: 10.1038/s41598-019-52241-2.

Ruijs, A., M. Kortelainen, G.A.A. Wossink, C.J.E. Schulp, and R. Alkemade. 2015. *Opportunity Cost Estimation of Ecosystem Services Environmental and Resource Economics*. Springer Netherlands. doi: 10.1007/s10640-015-9970-5.

Schleupner, C., and U.A. Schneider. 2013. “Allocation of European Wetland Restoration Options for Systematic Conservation Planning.” *Land Use Policy* 30(1). Elsevier Ltd: 604–614. doi: 10.1016/j.landusepol.2012.05.008.

Schou, J.S., J. Bladt, R. Ejrnæs, M.N. Thomsen, S.E. Vedel, and C. Fløjgaard. 2021. “Economic Assessment of Rewilding versus Agri-Environmental Nature Management.” *Ambio* 50(5): 1047–1057. doi: 10.1007/s13280-020-01423-8.

Senf, C., J. Sebald, and R. Seidl. 2021. “Increasing Canopy Mortality Affects the Future Demographic Structure of Europe’s Forests.” *One Earth* 4(5). Elsevier Inc.: 749–755. doi: 10.1016/j.oneear.2021.04.008.

Sinden, J.A. 2004. “Estimating the Opportunity Costs of Biodiversity Protection in the Brigalow Belt, New South Wales.” *Journal of Environmental Management* 70(4): 351–362. doi: 10.1016/j.jenvman.2003.12.013.

Smita Tale, K., and S. Ingole. 2015. “A Review on Role of Physico-Chemical Properties in Soil Quality.” *Chem Sci Rev Lett* 4(13): 57–66.

Spencer, D., Marques, A., Veerkamp, C., van der Marel, M., Verburg, P., Sarita Namasivayam, A., Di Marco, M., Jung, M., Kujala, H., Visconti, P., & Schipper, A. 2025. Opportunity cost estimates for spatial conservation prioritisation across Europe design. *Scientific Data*, *12*(1583). https://doi.org/10.3897/arphapreprints.e123365.

Špička, J., and P. Dereník. 2021. "How Opportunity Costs Change the View on the Viability of Farms? Empirical Evidence from the EU." *Agricultural Economics (Czech Republic)* 67(2): 41–50. doi: 10.17221/412/2020-AGRICECON.

Strange, N., C. Rahbek, J.K. Jepsen, and M.P. Lund. 2006. "Using Farmland Prices to Evaluate Cost-Efficiency of National versus Regional Reserve Selection in Denmark." *Biological Conservation* 128(4): 455–466. doi: 10.1016/j.biocon.2005.10.009.

Strassburg, B.B.N., A. Iribarrem, H.L. Beyer, C.L. Cordeiro, R. Crouzeilles, C.C. Jakovac, A. Braga Junqueira, E. Lacerda, A.E. Latawiec, A. Balmford, T.M. Brooks, S.H.M. Butchart, R.L. Chazdon, K.H. Erb, P. Brancalion, G. Buchanan, D. Cooper, S. Díaz, P.F. Donald, V. Kapos, D. Leclère, L. Miles, M. Obersteiner, C. Plutzar, C.A. Carlos, F.R. Scarano, and P. Visconti. 2020. "Global Priority Areas for Ecosystem Restoration." *Nature* 586(7831): 724–729. doi: 10.1038/s41586-020-2784-9.

Tajidan, T., and T. Sjah. 2015. "Producer Surplus as a Measure for Opportunity Cost: The Case of Corn Farming on the Hill of Mount Rinjani – Indonesia." *Advances in Management & Applied Economics* 5(3): 37–42. Available online at http://www.scienpress.com/Upload/AMAE/Vol 2_3_8.pdf.

Verkerk, P.J., C. Levers, T. Kuemmerle, M. Lindner, R. Valbuena, P.H. Verburg, and S. Zudin. 2015. "Mapping Wood Production in European Forests." *Forest Ecology and Management* 357. Elsevier B.V.: 228–238. doi: 10.1016/j.foreco.2015.08.007.

Visconti, P., L. O'Connor, and J. Beher. 2024. *Approaches to Identify Terrestrial Priority Areas for Achieving the 30% and 10% Protection Target in the EU*. doi: 10.5281/zenodo.14529890.

Weitzman, M.L. 1998. "Why the Far-Distant Future Should Be Discounted at Its Lowest Possible Rate." *Journal of Environmental Economics and Management* 36(3): 201–208. doi: 10.1006/jeem.1998.1052.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data, Second Edition*. MIT Press

Wooldridge, J.M. 2019. "Correlated Random Effects Models with Unbalanced Panels." *Journal of Econometrics* 211(1). Elsevier B.V.: 137–150. doi: 10.1016/j.jeconom.2018.12.010.

Yoon, H.S., and P.R. Armsworth. 2022. "Timing Land Protection to Exploit Favorable Market Conditions." *Biological Conservation* 270(April). Elsevier Ltd: 109566. doi: 10.1016/j.biocon.2022.109566.

Yu, Q., L. You, U. Wood-Sichra, Y. Ru, A.K.B. Joglekar, S. Fritz, W. Xiong, M. Lu, W. Wu, and P. Yang. 2020. "A Cultivated Planet in 2010-Part 2: The Global Gridded Agricultural-Production

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