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Soil Carbon Sequestration Following Natural Vegetation Recovery on Abandoned European Lands: Review and Research Needs

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ABSTRACT

Natural vegetation recovery of abandoned agricultural lands could play a significant role in combating climate change by enhancing carbon (C) sequestration over time in a passive and cost-effective manner. After agricultural land is abandoned, natural regeneration processes, such as the regrowth of tree cover and increased microbial activity, typically restore soil organic carbon (SOC) sinks, thereby capturing atmospheric carbon dioxide (CO_2). However, understanding its contribution to CO_2 removal, particularly, on a large, continental scale, remains limited. In this systematic review, we aimed to gather studies investigating soil C sequestration following the abandonment of agricultural activities across Europe. By conducting an integrative analysis of data from 36 studies focusing on natural vegetation recovery after agricultural abandonment, we assessed the relative changes in SOC over time in relation to various environmental factors. Our findings revealed that SOC dynamics are influenced by management, soil reference group, exposition (aspect), and forest type, with remarkable increases found in Mediterranean regions, certain soil groups (Regosols, Cambisols, Calcisols), cropland-converted broadleaf and mixed forests, and specific aspects (North, South, and South-West facing sites). However, the results were strongly influenced by the uneven geographical and altitudinal distribution of study sites, which varied in terms of previous land use management, significantly affecting sequestration models. Most studies concentrated on the Mediterranean region, with grassland data predominantly coming from higher elevations. As a result, we call attention to a pressing need for broader research across Europe and present results of a gap analysis of recently abandoned croplands, highlighting especially underrepresented regions such as Northern Spain, Central France, the United Kingdom, Germany, Poland, the Baltic states, Hungary, and the Balkans, where SOC dynamics remain poorly documented. These findings provide a roadmap for researchers and policymakers to prioritize future SOC monitoring and natural vegetation recovery initiatives to enhance soil C sequestration across Europe.

1 | Introduction

In 2023, atmospheric carbon dioxide (CO_2) concentrations surpassed 420 ppm (Global Monitoring Laboratory 2025) and climate change is approaching critical thresholds that could result in severe consequences unless immediate action is taken. Reaching net zero greenhouse gas (GHG) emissions by 2050 is the key to limiting global warming to 1.5°C and achieving the

Highlights

- This study synthesizes data on SOC dynamics in abandoned lands across Europe.
- Rewilding could promote soil carbon sequestration in a cost-effective way.
- SOC accumulation during rewilding varies strongly by environmental variables.
- Rewilded croplands show notable SOC increases compared to rewilded grasslands.
- More research is needed across Europe to assess C sequestration drivers over time.

targets set out in the Paris Agreement (2015). To this end, one of the most challenging aspects is not only the reduction of GHG emissions, but also the need for large scale "negative emissions" to offset the inability to fully eliminate all emissions from fossil fuels (Fuss et al. 2018). Recent estimates have shown that annual carbon (C) sequestration in forests accounts for nearly half of fossil fuel emissions globally and has been rising in temperate forests due to increases in forest area (Pan et al. 2024), driven by active reforestation and/or passive natural vegetation recovery efforts. Natural vegetation recovery can generally be defined as "reinstating natural processes that would have occurred in the absence of human activity" (Wentworth and Alison 2016). It is distinguished from restoration, which is a managed process of reinstating lost features to fully (or partly) return to the original state. Natural vegetation recovery of abandoned agricultural land is defined here as the recovery of shrubs and/or trees on cleared lands through spontaneous regrowth after the cessation of previous disturbance or land use (Cook-Patton et al. 2020). This process has been suggested to be a natural, effective, and low-cost C sink in both the above- and below-ground components of the terrestrial ecosystems, potentially helping to reduce the atmospheric CO_2 concentration and to fight climate change (Guo and Gifford 2002; Lal 2004; Cook-Patton et al. 2020). The process of agricultural land abandonment and its subsequent spontaneous development occur worldwide across various terrestrial ecosystems, under different climatic and environmental conditions (Rey Benayas et al. 2007; Campbell et al. 2008; Cramer et al. 2008; Queiroz et al. 2014). In Europe alone, the forest area increased by almost 14 million ha (+10%) in the period 1990–2020 (Eurostat. 2021) and it is estimated that between 10 and 29 million hectares of arable land will be abandoned between 2000 and 2030 (Verburg and Overmars 2009). This implies that most of this land might become available for active reforestation or passive natural vegetation recovery (Fayet et al. 2022), if policy makers provide natural vegetation recovery incentives that will stop recultivation.

However, a comprehensive assessment of the impacts of natural vegetation recovery on agricultural lands at large scale, such as across Europe, is lacking. To our knowledge, such studies have only been conducted in two biogeographical regions within Europe (Bárcena et al. 2014; Bell et al. 2021). Understanding the processes that influence C sequestration in abandoned agricultural areas is crucial for developing future protected areas and management strategies that promote soil health, maximize C sequestration, and favorable climate change scenarios.

In this systematic review, we searched and summarized studies focusing on soil C sequestration over time following the abandonment of agricultural activities in Europe and outlined their overall findings. First, we analyzed the current distribution of studies by biogeographical regions, previous land use, present or potential forest type, and soil unit. Through this analysis, we highlighted areas and broader environmental variables (EVs) where the number of studies remains insufficient.

Second, we estimated the relative change in soil organic carbon (SOC) over time since abandonment (TSA) by conducting an integrative data analysis of SOC stock data obtained from those specific studies focusing on natural vegetation recovery after agricultural abandonment. We compared this estimate across different types of biogeographical regions, soil reference groups, previous land use, forest types, and geographical aspects. This allowed us to assess potential differences in C sequestration rates driven by different environmental factors.

Third, through a gap analysis, we highlighted the geographical areas of Europe where data is still lacking to achieve a representative and detailed assessment of the soil C dynamics following agricultural abandonment. Finally, we propose future research directions and essential measurements that should be incorporated into all studies to gain a more comprehensive understanding of soil C stock changes during natural vegetation recovery. These insights will help support sustainable, low-cost land management and promote favorable climate change scenarios. While Europe is the primary focus region of our meta-analysis, gap assessment, and evaluation of SOC dynamics after natural vegetation recovery of abandoned lands, we also draw on global studies to provide a broader perspective on the underlying mechanisms.

2 | Materials and Methods

2.1 | Search Strategy, Selection of Studies, and Data Collection

In June 2024, we conducted a search for studies that examined changes in SOC over time in abandoned agricultural lands across Europe. The minimum data required from these studies included SOC stock and the corresponding TSA of the agricultural field where the SOC stock was measured. We searched for studies on two platforms: Web of Science Core collection (https://clarivate.com/academia-government/scientific-and-academic-research/research-discovery-and-referencing/web-of-science/) and Scopus (https://www.elsevier.com/products/scopus), with no restrictions on publication years and languages.

We used the following string of keywords, combined with Boolean operators and using the "topic" search option in the Web of Science platform (plus the "TS=" code which includes titles, abstracts and keywords): ("soil organic carbon" OR "SOC" OR "soil carbon") AND ("abandon*" OR "abandoned land" OR "land abandonment" OR "former agricultural land" OR "post-agriculture") AND ("Europe*" OR "European Union" OR "EU" OR "Germany" OR "France" OR "Spain" OR "Italy" OR "United Kingdom" OR "Poland" OR "Netherlands" OR "Sweden" OR "Norway" OR "Denmark" OR "Finland" OR "Greece" OR "Portugal" OR "Austria" OR "Switzerland" OR

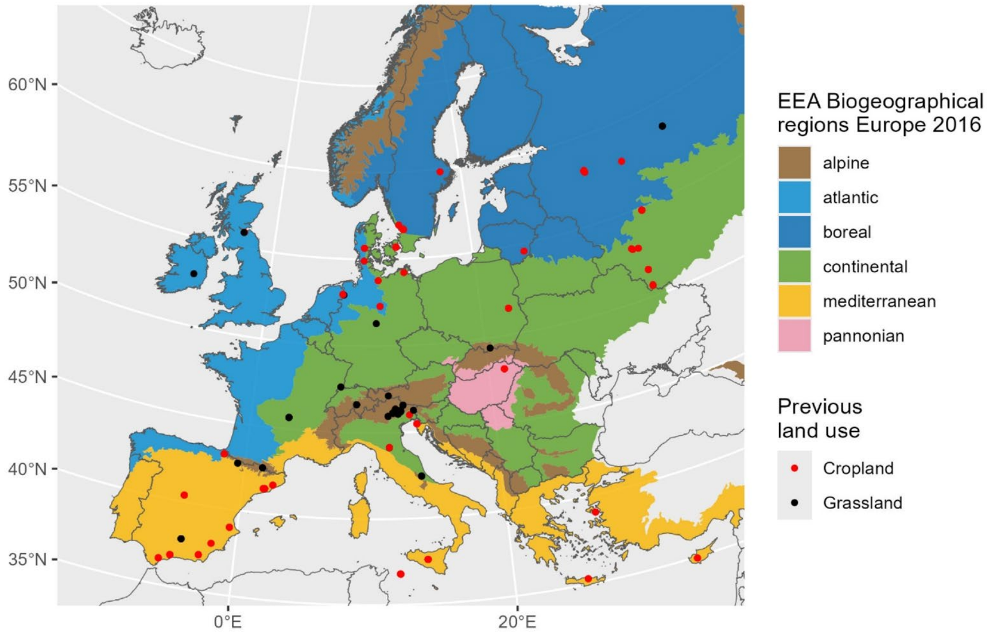

FIGURE 1 | Distribution of study sites across Europe and biogeographical regions included in the systematic review. The sites were categorized on the type of agricultural land use prior to abandonment. Some points on the map represent multiple adjacent sampling sites; however, since the exact coordinates of these sites were not provided in the selected studies, they are shown as a representative point.

"Czech Republic" OR "Hungary" OR "Ireland" OR "Belgium" OR "Romania" OR "Bulgaria" OR "Croatia" OR "Slovakia" OR "Slovenia" OR "Lithuania" OR "Latvia" OR "Estonia" OR "Luxembourg" OR "Cyprus" OR "Malta" OR "Bosnia & Hercegovina" OR "Ukraine" OR "Russia" OR "Serbia" OR "Albania" OR "Belarus"). Additionally, we identified several studies within a review paper focused on the same topic for Northern Europe (Bárcena et al. 2014) and from a YSSP report from the International Institute for Applied Systems Analysis (Bell et al. 2021).

As a result of our platform search, we retrieved 196 and 197 manuscripts from Web of Science Core collection and Scopus, respectively, which we then filtered through several steps. First, we removed duplicates from different sources. Next, we individually reviewed the titles, abstracts, and main texts of over 200 manuscripts, excluding those that did not include both SOC stock and TSA for at least two sites. We also examined which of these manuscripts focused specifically on studying agricultural lands that were entirely abandoned, with no human activities occurring after abandonment (i.e., natural secondary succession, afforestation). In this way, we excluded studies that measured soil characteristics in abandoned agricultural lands where, even after abandonment, activities such as mowing, tillage, or artificial afforestation with young trees were carried out. Furthermore, we verified that all the studies included data from a control site (i.e., agricultural field) or a site that had been abandoned within the past 10 years, allowing us to later standardize the change in SOC. Additionally, all studies were required to provide SOC measurement for at least the top 10 cm of soil depth and beyond. To ensure a standardized review process, all manuscripts were evaluated for quality twice—once by each author responsible for the screening (M.T.K.N. and D.G.). We did not focus on the laboratory methods used to determine soil organic C content, as we primarily relied on relative data for modeling purposes (see below).

Through this screening process, we identified 36 studies that fully met our criteria (Table S1). From these studies, we extracted the following values for each sampling site: SOC stock, TSA, coordinates, biogeographical region, land use prior to abandonment, study design, forest type, soil reference group and aspect. This resulted in 267 unique observations (sites) without control sites, which were used for further relative change calculations (Figure 1). Although the primary criteria for selection of studies were methodological (i.e., SOC and TSA availability, no human intervention postabandonment and comparable soil depth intervals), we accounted for spatial variability by ensuring that selected studies encompassed different biogeographical regions across Europe. We checked the spatial representativeness of the dataset by verifying that each biogeographic region included a minimum of 10 sites taken from more than one study to implement meaningful statistical comparisons. This strategy enabled us to address spatial variability and reduce regional biases within the limitations of the available literature.

We initially aimed to collect additional information, particularly, continuous variables such as altitude, mean annual precipitation, mean annual temperature, and soil pH. However, these variables were not consistently available across all studies for all sites. We also considered obtaining these data from publicly available raster layers that simulate such information for all of Europe, but we lacked the coordinates of all individual sampling sites, which would be necessary to retrieve the data. Since the generalized linear mixed effect model (GLMM) we intended to use does not accommodate missing data (i.e., it excludes rows with missing values) and given that our dataset is already constrained by sample size, we decided not to include continuous variables in this analysis.

The SOC stock values (our response variable) were reported in different units across the studies. To standardize the SOC values, we calculated SOC stocks ($\mathrm{Mg\,C\,ha^{-1}}$) using one of the following equations:

$$\mathrm{SOC}\left(\mathrm{Mg\,ha^{-1}}\right)=\mathrm{SOC}\,(\%)\times\text{bulk density}\left(\mathrm{g\,cm^{-3}}\right)\times\text{depth (cm)}\times 0.1 \tag{1}$$

$$\mathrm{SOC}\left(\mathrm{Mg\,ha^{-1}}\right)=\mathrm{SOC}\left(\mathrm{g\,kg^{-1}}\right)\times\text{bulk density}\left(\mathrm{g\,cm^{-3}}\right)\times\text{depth (cm)}\times 0.01 \tag{2}$$

$$\mathrm{SOC}\left(\mathrm{Mg\,ha^{-1}}\right)=\mathrm{SOC}\left(\mathrm{g\,m^{-2}}\right)\times 0.01 \tag{3}$$

$$\mathrm{SOC}\left(\mathrm{Mg\,ha^{-1}}\right)=\mathrm{SOC}\left(\mathrm{kg\,m^{-2}}\right)\times 10 \tag{4}$$

After standardizing SOC stock values for all sites, we used a log-transformed relative change in SOC to quantify the percentage change in SOC between afforested sites and corresponding controls for each chronosequence or paired plot sites (Hedges et al. 1999; Bárcena et al. 2014):

$$\ln(\mathrm{RSC})=\ln\left(\frac{\overline{X}_{\mathrm{Aff}}}{\overline{X}_{\mathrm{Control}}}\right) \tag{5}$$

where RSC is relative SOC change, $\overline{X}_{\mathrm{Aff}}$ is the mean SOC stock of the naturally afforested site (i.e., site that was abandoned) $\overline{X}_{\mathrm{Control}}$ is the mean SOC stock of the corresponding control site. In this way, we standardized the SOC stock change over time for measurements taken with different devices and at varying depths ranging from 10 to 30 cm.

Initially, we aimed to conduct a meta-analysis for this manuscript, with the primary goal of collecting the mean SOC values and their corresponding variances for each sampling site. However, for a number of studies, we were unable to obtain either the standard deviations or the individual measurements of each soil sample, and only the mean SOC stock values for each site were provided. As a result, we performed an integrative data analysis, combining all the mean RSC values for each site into a single dataset, treating them as individual sample points. We accounted for the random effects of neighboring sites and the influence of the study design.

The TSA (years) was generally easily extracted from each manuscript. In few cases, the year of abandonment was given as a range, as the authors were uncertain about the exact abandonment date but knew the land had been abandoned between two specific years when maps or orthophotos were available. This occurred only for the oldest study site in the chronosequence. In such instances, we calculated TSA as the difference between the midpoint of the reported year range and the year of soil sampling. In several studies with a chronosequence design, there was no control group (i.e., agricultural land), but there was a site abandoned within 10 years or less before sampling. In such cases, we used this site as the control and adjusted the TSA of other sites accordingly.

The previous land use variable (a categorical variable) indicates whether the agricultural land was cropland or grassland before abandonment. Croplands are here defined as any agricultural land used for growing crops, while grasslands refer to agricultural lands designated for grazing (as per EU regulation laws: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02018R0841-20230511).

The biogeographical regions variable (a categorical variable) was classified based on the coordinates of the sampling site using the European Environment Agency's classification for biogeographical regions (https://www.eea.europa.eu/en/analysis/maps-and-charts/biogeographical-regions-in-europe-2?activeTab=a7caf3b5-7254-4a24-8919-693d4115158b).

For the study design variable, we categorized the observations based on how the study was structured to collect data of SOC change over time. Most studies were designed as chronosequence (space-for-time substitutions), while others used paired plots, where one site had been abandoned for a specific period and was compared to an adjacent control plot (agricultural land). Only one study followed the same sampling site over several decades, and it was excluded from our analysis due to the small sample size, which would have limited the ability to test the effect of study design in the statistical analysis.

The forest-type variable was created based on the tree vegetation description of the forests in older sampling sites in each study (typically sites over 20 years old). Forests were classified as either broadleaf, coniferous, or mixed. If the studies indicated that the dominating tree vegetation was a mix of broadleaf and coniferous trees, we classified it as a mixed forest. For sites with a relatively short TSA (from 5 to 30 years), we assigned the same forest type as the accompanying older sites in the same chronosequence or paired plot. This assumption was based on the expectation that the future dominant forest type will be the same as the older sites in the same chronosequence or study due to their proximity. One study used paired plots in abandoned agricultural areas across Europe. In this case, for the younger abandoned sites, we recorded the tree type mentioned as the closest vegetation.

2.2 | Data Exploration

For data exploration, we followed the general protocol outlined by Zuur et al. (2010). Both the RSC and TSA variables were not normally distributed and were right-skewed, so we log-transformed them to normalize their distribution. To balance the factor levels, we removed all "soil reference group" levels with fewer than 10 observations, as well as the Pannonian level in the "biogeographical region" which had only 5 observations, all from a single site.

We assessed collinearity among the categorical variables using the Cramer's V test, setting the threshold for collinearity at $\varphi_c = 0.5$. Introducing highly correlated predictors in a regression model can lead to misleading statistical analysis. For example, removing one covariate may make others appear significant or alter the direction of their estimated effects (Zuur et al. 2010). The "biogeographical region" was correlated with both the "soil reference group" ($\varphi_c = 0.55$) and "previous land use" ($\varphi_c = 0.74$), while the "soil reference group" was also correlated with "previous land use" ($\varphi_c = 0.56$). Since all three variables were correlated with each other, and due to the small sample size in many categorical levels—especially when investigating interactions, which led to rank deficiency (Figure S1)—we decided to run four separate models, each incorporating one or two explanatory categorical variables.

2.3 | Statistical Analyses—Finding Important Trend-Affecting Variables

We performed all analyses and calculations in R version 4.3.3 (R Core Team 2024). We used GLMM from the *lme4* package (Bates et al. 2015) with Gaussian error structure. We examined how each level of the categorical variable influenced the relationship (trend) between RSC and TSA. Due to the small dataset and concerns about possible overfitting, we did not examine interactions between variable levels, except for the interaction between "previous land use" and "forest type," as it had sufficient data for each level of interaction. In the final four models, we analyzed how the SOC trend changes over time across different: (1) biogeographical regions, (2) soil reference groups, (3) previous land uses and forest types, and (4) aspect positions. The structure of the models with a single categorical variable, in R notation, was as follows:

$$\mathrm{Log}\,(\mathrm{RSC}) \sim \log\,(\mathrm{TSA})\text{: categorical\_variable} + (1|\,\text{place\_id}) + (1|\,\text{study\_design}),$$

while for the interaction between "previous land use" and "forest type" it was:

$$\log\,(\mathrm{RSC}) \sim \log\,(\mathrm{TSA})\text{: prev\_land\_use: forest\_type} + (1|\,\text{place\_id}) + (1|\,\text{study\_design})$$

The random component (1|place_id) of the model enabled us to account for observations sampled in proximity or within the same study design. Given that the studies were designed as either paired plots or chronosequences, we assumed that SOC changes within the same study or area would be more similar to each other.

We validated the models by creating standard validation plots using the R package *performance* (version 0.12.3). The residuals were not normally distributed, even after variable transformation and using both normal and gamma error structures with log link. To address this, we confirmed the significance of our level-differences using the *robustlmm* package (Köller 2016) where we fitted the log-normal model that was more robust to violations of assumptions by down-weighting outliers. The significant level interactions were consistent with those obtained from the regular GLMM model.

The ln(RSC) ~ ln(TSA) estimates represent the slopes of this linear relationship, and if they were back transformed using the "exp" function, they would represent the exponent of the response variable (i.e., $\mathrm{RSC}=\mathrm{TSA}^{\mathrm{estimate}}$). Therefore, for easier comprehension, we calculated the average RSC increase after 100 years since agricultural abandonment (TSA = 100). For plotting, we used the *ggplot2* package (version 3.5.1; Wickham 2016). For the visualizing study sites, we utilized the *tmap* package (version 3.3.4; Tennekes 2018) in conjunction with the *terra* package (version 1.7.78; Hijmans 2024) to convert the coordinates into shape files.

2.4 | Gap Analysis

The number of studies focusing on SOC change over TSA was relatively low, particularly in certain biogeographical regions, such as the Boreal, Atlantic, and Pannonian regions. To provide recommendations for future research and the establishment of new chronosequences which are crucial for obtaining a comprehensive and accurate picture of the effects, we conducted a gap analysis to identify areas where informative SOC data are still lacking across environmental gradients within Europe. Based on the findings of the previous analysis, we decided to focus separately on abandoned croplands and abandoned grasslands, as they showed different trends in SOC change and warrant further separate attention—croplands as a C sink, while grasslands as potential SOC-loss areas after abandonment.

To do this, we created two rasters of the recently abandoned agricultural areas of arable land (cropland in our paper) and pasture (grassland in our paper) areas abandoned between 2000 and 2018, using CORINE Land Cover raster layers (European Environment 2020). First, absolute abandonment was elaborated by selecting all pixels that were classified in the CORINE Land Cover rasters as arable lands or pastures, respectively, in 2000 (2.1 and 2.3 classes under 2. Agricultural areas in CORINE Land Cover classes), and were covered by a (semi-)natural land cover in 2018 (all classes under 3. Forest and seminatural areas, 4. Wetlands, and 5. Water bodies). Second, relative abandonment was calculated by dividing absolute abandonment values by the total 1 km^2 grid area in year 2000. Relative abandonment serves as a metric for the intensity of abandonment processes in a given region for both land cover types. The final two rasters provide data on the relative abandonment of each 1 km^2 grid cell, showing the percentage of abandoned cropland in each grid.

We acknowledge that these abandoned croplands are relatively newly abandoned compared to the time required for a forest to develop. However, we assumed that older abandoned areas with a longer TSA exist nearby these newly abandoned areas as abandonment in many places in Europe is a gradual process that has already lasted for several decades. Additionally, we recognize the limitations of CORINE land cover products in detecting land use changes (Büttner 2014; Bachantourian et al. 2022; Gallardo and Cocero 2023) and, thus, misclassifications should be considered. Since each dataset used in this study carries its own source-specific uncertainties, we compiled multiple data sources to partially mitigate these limitations. Nevertheless, the overall hotspots of land abandonment are expected to be accurately captured using this approach.

The number of grid cells of 1 km^2 containing abandoned cropland or grassland exceeded 424,369 and 269,000, respectively. To compare this dataset with the 181 points and 86 points for cropland and grassland sites, respectively, (totaling to 267 sites from all collected studies), we needed to reduce the grid sample size while still ensuring it represented most of Europe. When relative abandonment was visualized on a histogram, most data fell below 10% relative abandonment per 1 km^2 grid cell (i.e., less than 10 ha, Figures S2 and S3). These cells with a small percentage of abandoned land were removed from further gap analysis, as they likely represent border areas surrounding larger abandoned sites. Additionally, larger sites generally have a higher likelihood of experiencing abandonment at different times, making it easier to create chronosequences for future studies. Larger sites also offer more space for standardized measurements that are less affected by edge effects from surrounding landscapes (Riutta et al. 2016; Cardelús et al. 2020). After this filtering, only 18.5% of the grid cells remained for croplands, and 12.6% for grasslands. However, the abandoned land area, that was included in these grid cells, covered 50.4% and 67.8% of the total abandoned land area and were distributed across Europe, as shown in Figure 5a,b. Despite the reduction, the filtered dataset still consisted of over 35,800 and 34,000 grid cells for croplands and grasslands, respectively. For the abandoned cropland data, we further applied random subsampling by selecting a 50% subsample from this filtered dataset to enhance the visibility of differences across the gradients in the generalized additive model (GAM) results and to improve the visibility of the data points on the map. We then used the newly obtained ratio between abandoned lands and our datasets for croplands (17,935 abandoned grids/181 review sites = 99) to create the same dataset ratio for grasslands and obtain comparable thresholds (86 review sites × 99 = 8514 abandoned grids).

After obtaining the smaller datasets for each land use management, we combined the coordinates of the abandoned grid cells with those of our data. We added a column where the abandoned grid cells were assigned a value of 1, while our dataset was assigned a value of 0. This allowed us to create a response variable that we could use for the GAM analysis, enabling predictions on the probability of having sufficient data across different environmental gradients.

The next step involved obtaining common EVs for soil and the environment that are available across most of Europe. We created raster layers for the following five EVs: average annual temperature, average annual precipitation, elevation, soil pH, and cation exchange capacity. Climate data were sourced from downscaled data in the Chelsa dataset (Karger et al. 2017), while soil data were obtained from Ballabio et al. (2019). These data were then projected and resampled to the common 1 km^2 grid.

Using the created raster layers, we extracted the values for each of the EVs based on the coordinates of our review data points and the abandoned areas. This allowed us to obtain the exact values for all the EVs at the coordinates we wanted to compare. These EVs were then used as explanatory variables in our model.

All data preparation and analyses were conducted in R (version 4.3.3; R Core Team 2024). Our goal was to examine how the probability changes between our dataset and the abandoned cropland dataset across the EV gradients. We performed GAM models with quasibinomial error structure using the *mgcv* package (Wood 2017) as the data were under-dispersed (Pekár and Brabec 2020). Each of the five models differed only in the explanatory variable, which was one of the EVs. This approach allowed us to estimate the probability of data insufficiency along different segments of the EV gradient (see figures and S5 for clarification). The probabilities were derived from each model by running the "predict ()" function with argument "type = 'response'."

We then selected an arbitrary probability threshold for identifying important coordinates, primarily based on how to best visualize the data. This required a trade-off between ensuring broad coverage across Europe while also highlighting areas that are more relevant for future samplings. Even after two rounds of reduction, the datasets of abandoned croplands and grasslands had 99 times more observations than our dataset (21,027 vs. 181 observations for croplands and 9990 vs. 86 observations for grasslands). As a result, the probabilities of data insufficiency were consistently over 99% across most of the EV gradient. After testing a range of thresholds and visualizing the results on the maps, we chose a 99% threshold to eliminate all coordinates below this level, considering them unimportant. Despite using such a high threshold, we still retained between 3000 and 10,000 important coordinates for each of the five GAM models. This removal was performed separately for each GAM model, and then we combined all the coordinates into a single data frame. To illustrate how the threshold influences the visualization of important sites, we included two additional maps for each land use management in the Appendix A: one with a 98.5% threshold and another with a 99.5% threshold (Figures S6 and S7 for croplands, Figures S8 and S9 for grasslands).

Identical coordinates obtained from the individual models were grouped together, and their frequency was summarized in a column called "importance level." The importance level was defined as the number of times a coordinate exceeded the 99% probability threshold, with values ranging from 1 to 5, corresponding to the five models. For example, an importance level of 3 indicates that the coordinate exceeded the threshold in three out of five models (i.e., in three of the EV gradients). The more frequently a coordinate exceeds the probability threshold across the models, the more important it is for future sampling. The final set of important coordinates was then visualized on a map of Europe, sourced from the EUROSTAT website (https://ec.europa.eu/eurostat/web/gisco/geodata/administrative-units/countries).

For data preparation, we used the *dplyr* package (version 1.1.4; Wickham et al. 2023). Probability plots were visualized using the *ggplot2* package (version 3.5.1; Wickham 2016). To visualize the important abandoned areas, we employed the *tmap* package (version 3.3.4; Tennekes 2018), with the "*terra*" package (version 1.7.78; Hijmans 2024) for transforming coordinates into shapefiles. The complete R script for data preparation and analysis is available in the Supporting Information (files "meta_analysis_script.r" and "gap_analysis_script.r").

3 | Results

3.1 | General Observations

We extracted 267 unique mean relative SOC change (RSC) values from different periods following agricultural abandonment, all derived from 36 studies (Table S1). The TSA ranged from 1 to

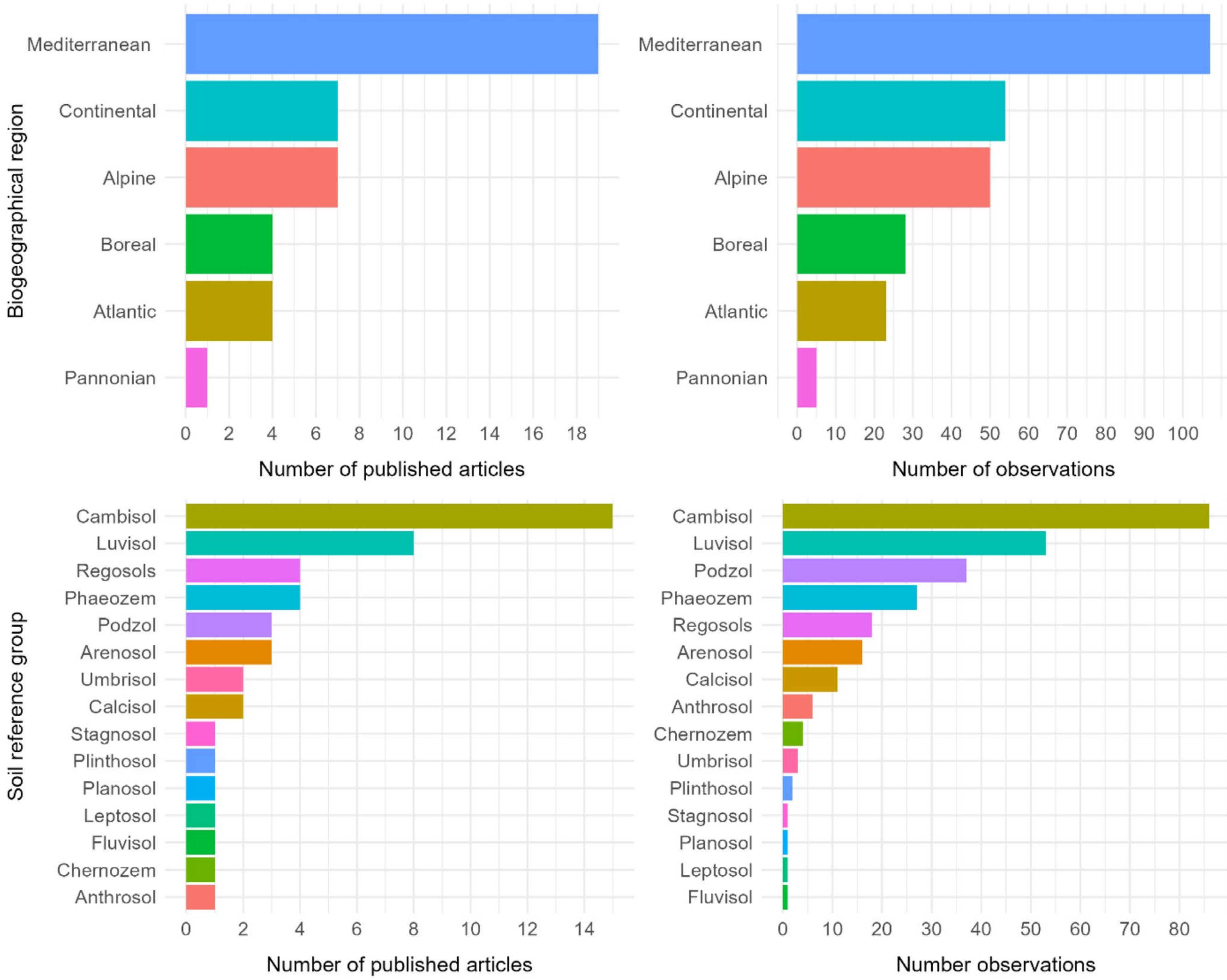

FIGURE 2 | Number of published articles and observations, categorized by biogeographical region and soil unit.

167 years, with the majority of the observations falling between 1 and 75 years (Figure S10). Over 50% of the studies focused on abandoned agricultural areas within the Mediterranean biogeographical region, while the fewest studies were conducted in the Atlantic, Boreal, and Pannonian biogeographical regions (Figures 1 and 2). Most of the samples were collected from Cambisols and Luvisols, which are the most common agricultural soils in Europe (Figure 2).

Among all the study sites, 181 were sampled on abandoned croplands, while 86 were sampled on abandoned grasslands (Figure 3). For both previous land use types, the most common forest type that has naturally grown, or is likely to grow, is broadleaf forest, followed by coniferous and mixed forests (Figure 3).

3.2 | SOC Stock Trends Over TSA

The GLMM model, which included only the biogeographical region in interaction with the trend, revealed a strong effect of individual biogeographical regions on the RSC-TSA relationship (GLMM-log, $F_{7,126.8} = 5.8$, $p < 0.001$; Figure 4a). Only the growth trend (slope) of the Mediterranean biogeographical region was significantly larger than zero (GLMM-log, estimate = 0.18, SE = 0.04, $T_{254.61} = 4.01$, $p < 0.001$), having a mean slope estimate (exponent) of 0.18 and intercept of 3.48, which after power-law calculation indicates an average 75% increase in SOC over a 100 years period. No other biogeographical regions showed a significant trend.

The GLMM model, which included only soil reference groups included in interaction with the trend, showed a strong effect of individual soil reference groups on the RSC–TSA relationship (GLMM-log, $F_{7,132} = 5.9$, $p < 0.001$, Figure 4b). The growth trend (slope) was significantly greater than zero for Regosols (GLMM-log, estimate = 0.17, SE = 0.07, $T_{238.33} = 2.37$, $p = 0.02$), Cambisols (GLMM-log, estimate = 0.19, SE = 0.05, $T_{237} = 4.05$, $p < 0.001$), and Calcisols (GLMM-log, estimate = 0.35, SE = 0.09, $T_{84.34} = 3.73$, $p < 0.001$), which after power-law calculation indicate an average 90%, 98%, and 210% increase in SOC over a 100 year period, respectively. Other soil reference groups did not show a significant trend. The GLMM model, which included previous land use and forest type in interaction with the trend, revealed a strong interaction between previous land use and forest type in affecting the RSC-TSA relationship (GLMM-log, $F_{6,222.5} = 12.0$, $p < 0.001$;

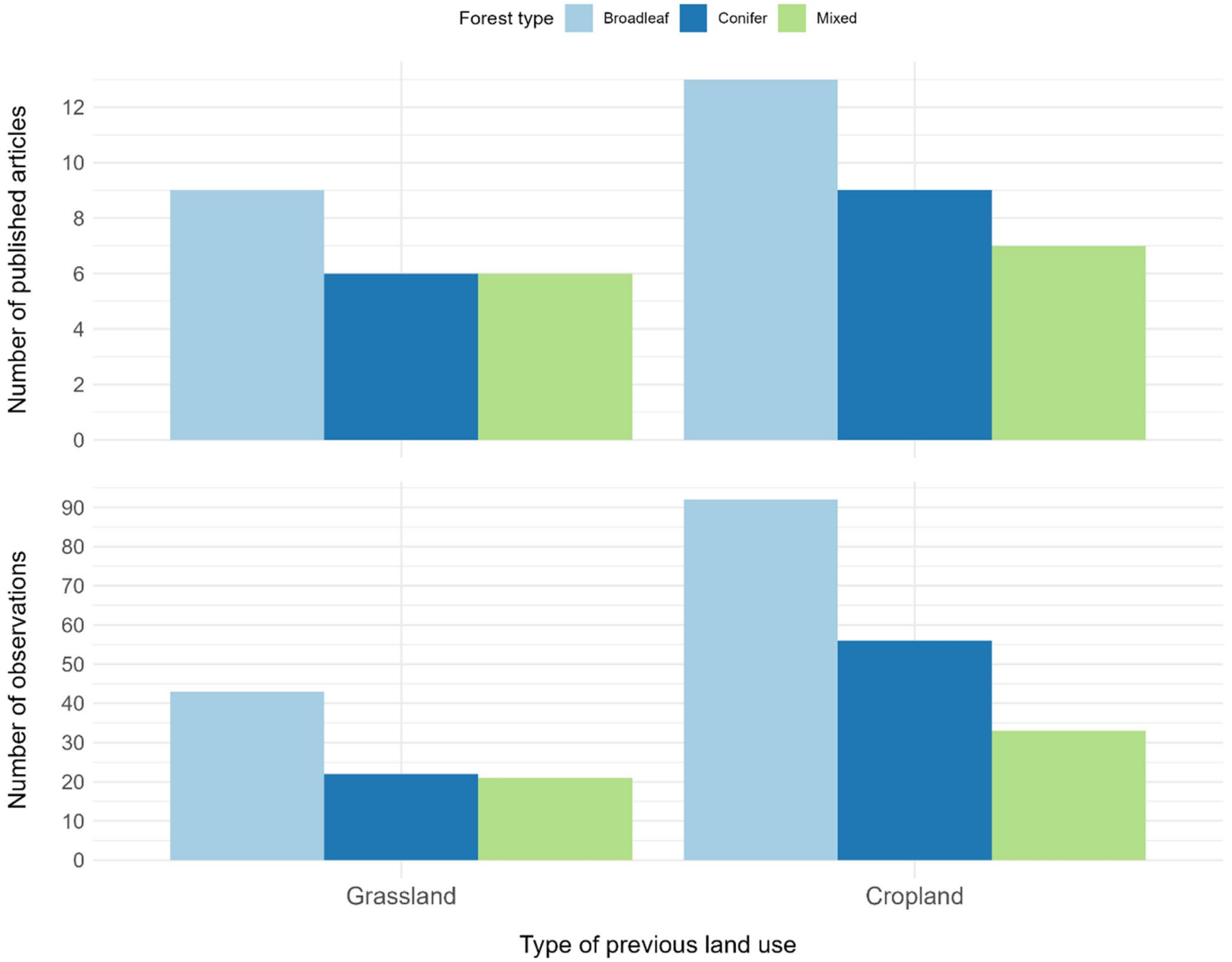

FIGURE 3 | Number of published articles and observations, categorized by previous land use prior to abandonment and the forest type that has naturally grown or is likely to grow.

Figure 4c). The growth trend (slope) was significantly greater than zero for Cropland: Broadleaf (GLMM-log, estimate = 0.17, SE = 0.04, $T_{249.1} = 4$, $p < 0.001$) and Cropland: Mixed forests (GLMM-log, estimate = 0.29, SE = 0.05, $T_{237.12} = 5.5$, $p < 0.001$), which after a power-law calculation indicate an average 97% and 176% increase in SOC over a 100 year period, respectively. No other interaction levels showed significant trends.

The final GLMM model with aspect included in interaction with the trend was marginally significant (GLMM-log, $F_{8,239.5} = 2.4$, $p = 0.02$, Figure 4d). The growth trends of North-facing (GLMM-log, estimate = 0.10, SE = 0.05, $T_{226.1} = 2.3$, $p = 0.024$), South-facing (GLMM-log, estimate = 0.11, SE = 0.05, $T_{251} = 2.3$, $p = 0.023$), and South-West-facing (GLMM-log, estimate = 0.15, SE = 0.05, $T_{257.6} = 2.86$, $p = 0.005$) sites were significantly greater than zero, which after a power-law calculation indicates an average of 74%, 78%, and 94% increase in SOC over a 100 year period, respectively. The growth trends of West-facing (GLMM-log, estimate = 0.13, SE = 0.07, $T_{231.5} = 1.7$, $p = 0.09$) and North-West-facing (GLMM-log, estimate = 0.11, SE = 0.06, $T_{246.3} = 1.9$, $p = 0.06$) sites were marginally nonsignificant. The more East-facing sites (South-East, North-East, and East) showed low yearly mean SOC increases or even decreases, but these trends were not significantly different from zero.

3.3 | Spatial Analyses and Priorities for Future Research on Croplands and Grasslands (Gap Analysis)

Figure 5a shows that, with a 99% probability threshold, the key areas of abandoned croplands that should be prioritized for future SOC change research are located in central and western Spain, central France, southern United Kingdom, central and eastern Balkans, western Germany, Northern Poland, the Baltic states, and Southern Finland. Figure 5b shows that, with a 99% probability threshold, the key areas of abandoned grasslands that should be prioritized for future SOC change research are located in northern Spain, central France, the whole of Ireland, northern and western United Kingdom, northern Netherlands, and Germany, most of Poland, eastern Latvia, and central Balkans.

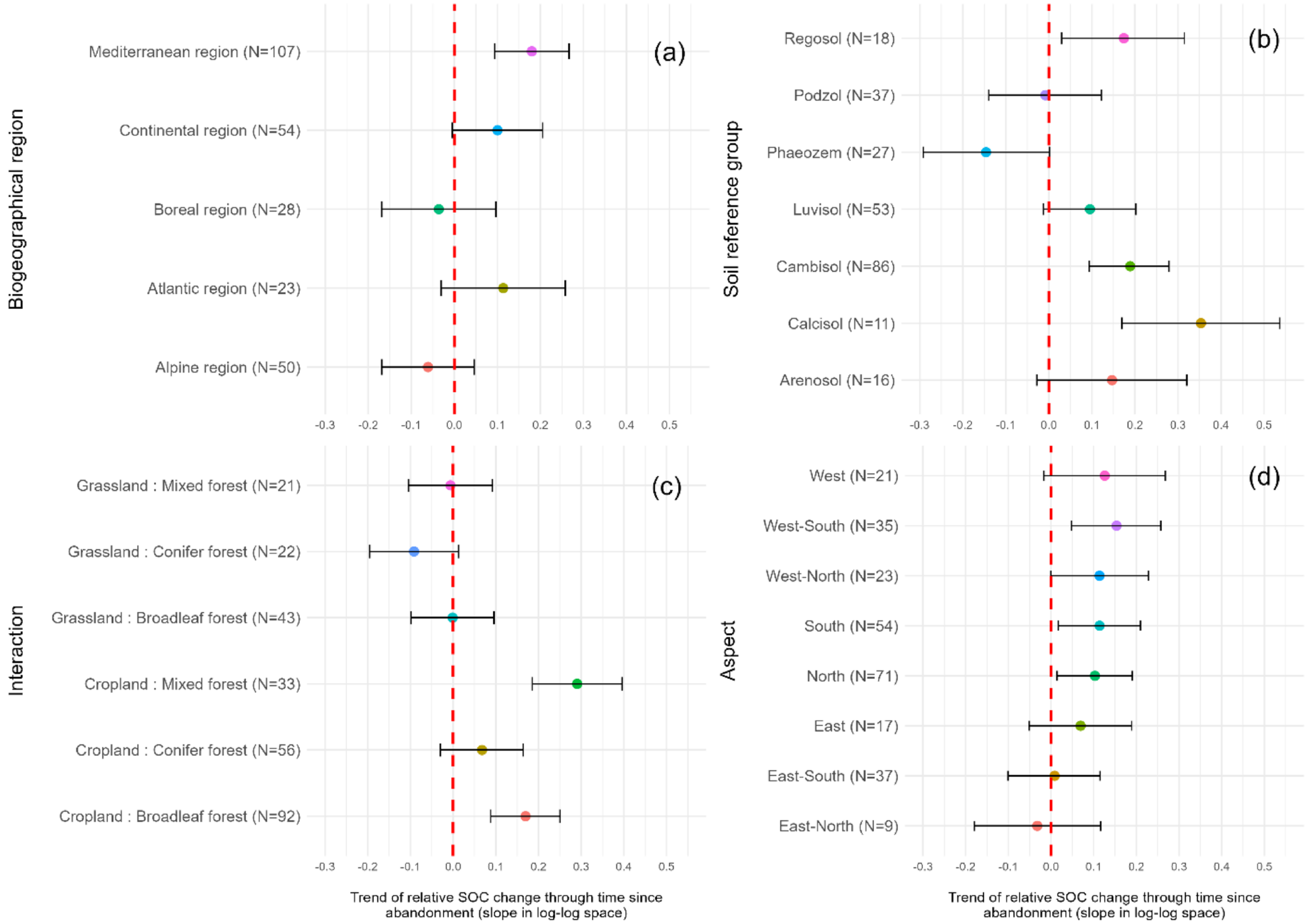

FIGURE 4 | Change in SOC (% per year after abandonment) in abandoned agricultural lands across Europe, categorized by (a) biogeographical region where the samples were collected, (b) the soil reference group of the sampling site, (c) interaction of previous agricultural management and forest type, and (d) aspect of the sampling site. The colored dots represent the mean slope value of the relationship in log–log space, and the black horizontal lines represent the 95% confidence interval (CI). Values in parenthesis indicate the sample size for each subgroup.

4 | Discussion

4.1 | Impact of Environmental Variables on Gain and Loss of SOC After Agricultural Abandonment

Briefly, we strictly aimed for studies with at least two variables, clear documentation of SOC stocks (i.e., SOC concentrations along with soil bulk density or calculated SOC stocks) and TSA, with no postabandonment human intervention. By this strategy, we ensured homogeneity of the data. The consequent predominance of Mediterranean studies shows both historical and recent land abandonment trends while data for other biogeographic regions (i.e., Atlantic, Boreal and Pannonian) remain scarce, probably because of less land abandonment frequencies or less research activities in these regions.

This scarcity of data for some biogeographic regions limits our comprehensive understanding of the SOC dynamics across the EU, considering that environmental gradients in temperature, moisture, vegetation composition and diversity, topographic features, and soil biogeochemical properties strongly influence SOC dynamics in abandoned land soils. The variability of SOC stocks across different regions highlights the importance of implementing region-specific land management strategies to optimize C sequestration.

Previous land-use type and forest type are among the most decisive factors influencing the trend of SOC change. Consistent with the findings of Guo and Gifford (2002), we observed significant SOC gains in abandoned croplands transitioning into broadleaf or mixed forests (Figure 4c). The SOC increase varied between forest types within the range of 97%–176% over a century, driven by differences in the increase in litter input and root biomass characteristics of these forest types. In contrast, grasslands do not exhibit similar SOC enrichment over time, showing no change or even a slight decrease (Figure 4c), though this trend was not significant. This result indicates that SOC sequestration in abandoned grasslands is typically negligible. The lack of significant SOC sequestration in abandoned grasslands can be attributed to the environmental conditions of the study sites and the sampling strategy of the included studies. According to Jobbágy and Jackson (2000), in the top 100 cm of soil profiles, SOC in grasslands is primarily stored in deeper layers (about 58%, > 20 cm), whereas, in forest soils, half of the total SOC in the top 100 cm is stored within the first 20 cm. This highlights the importance of grassland

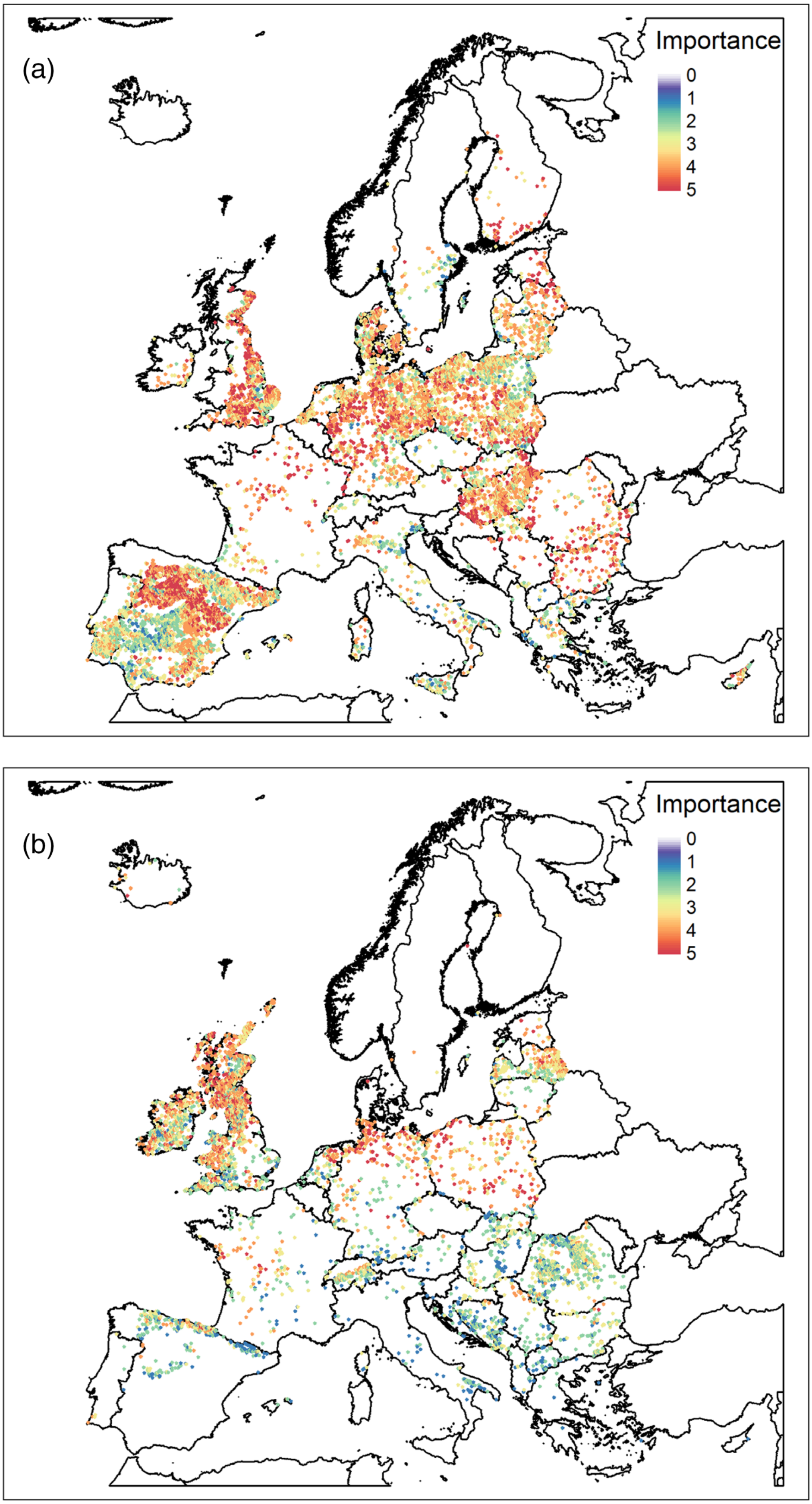

FIGURE 5 | Legend on next page.

FIGURE 5 | Map of Europe showing areas with (a) croplands and (b) grasslands that were abandoned between the years 2000 and 2018. Each dot presents an abandoned area, colored according to its importance as a future sampling site. The importance level was calculated based on a 99% probability threshold for lacking data across one to five environmental gradients (mean annual precipitation, mean annual temperature, elevation, soil, pH, or CEC). The importance level increases depending on the number of gradients with missing data. The dots on the map have been enlarged for better visualization and do not represent the original sizes of the 1 km^2 patches of abandoned land extracted from the Corine land cover raster layers.

rooting systems in promoting SOC formation in deeper soil layers (Guo and Gifford 2002). However, most of the studies in grassland soils focused on topsoil layers and overlooked the deeper depth intervals (Jobbágy and Jackson 2000; Jackson et al. 2002). In addition, the majority of the abandoned grassland sites included in our study (Figure S1) are located in high altitudes and the Alpine biogeographical region over Cambisols and Phaeozems soil reference groups, which might limit the SOC sequestration rates in the study sites (Laganière et al. 2010; Nadal-Romero et al. 2021). Therefore, future works need to investigate abandoned grasslands across diverse environmental gradients and deeper soil profiles to capture potential SOC dynamics following abandonment.

In contrast to grassland soils, we found that natural vegetation recovery of abandoned croplands across Europe led to a positive change of SOC over time, indicating C sequestration from the atmosphere (Figure 4c). Cropland soils are mechanically disturbed by tillage, which is closely associated with soil opening and aeration, potentially increasing heterotrophic respiration. Abandoning these practices and increasing the C input through litterfall can foster the sequestration of organic C in the soil. The detected higher C sequestration in abandoned croplands that transitioned to mixed forests than broadleaf and conifer forests may be attributed to variations in organic inputs, litter quality, rooting system, and tree growth.

In coniferous forests, the slower buildup of SOC than the other forest types (Figure 4c) can be attributed to the production of low-quality-slow-decomposing litter (e.g., pine needles) (Prescott 2002). Furthermore, converting croplands to deciduous broadleaf forests led to a smaller decline in SOC accumulation over time than in mixed forests. This may be linked to a more rapid decomposition of sole broadleaf litter compared to mixed broadleaf and coniferous litter, which reduces the turnover of recalcitrant organic C and slows long-term SOC sequestration (Tian and Takeda 1998; Růžek et al. 2021).

Similarly to our findings, Laganière et al. (2010) and Paul et al. (2002) suggested that the transition from cropland to mixed forest leads to SOC accumulation, likely due to increased organic inputs and complex rooting systems, which in turn promote higher microbial activity and SOM formation. Devi (2021), Qin et al. (2024), and Wang et al. (2016) concluded that different tree species and composition follow distinct C allocation strategies, which influences the rate, quantity, and quality of the organic inputs to the soil. They found that mixed-species forest soils typically store higher SOC levels than mono-species forests. However, studies on the influence of forest stand compositions (e.g., coniferous vs. broadleaved forests) on SOC stocks have yielded contradictory results. Some show that SOC stock is generally higher in broadleaved compared to coniferous forests (Niu et al. 2009; Wang et al. 2010; Hou et al. 2020), while others found that broadleaved forests store relatively lower SOC stocks than coniferous forests (Kasel and Bennett 2007; Schulp et al. 2008). The comprehensive review by Vesterdal et al. (2013), which examined common garden experiments, retrospective paired stand studies, and retrospective single-tree studies, provided evidence of consistent tree species effects on SOC stocks, particularly for forest floor carbon. The review found higher SOC values in broadleaved forests compared to coniferous forests. Regarding the role of tree species diversity, several studies have reported a positive relationship between C sequestration, both above- and below-ground, and species richness (Liu et al. 2018) and/or functional diversity (Palandrani and Alberti 2020). Similar results were found by Dawud et al. (2017) in a study across six major European forest types, although their findings highlighted a stronger influence of tree species functional groups and region-specific EVs.

Other environmental factors such as soil bedrock lithology (Heckman et al. 2009; Karimi Nezhad et al. 2024) impact SOC and nitrogen dynamics. Soil geochemical properties influence SOC preservation via the content of clay-sized particles (Jindaluang et al. 2013), clay mineralogy (Powers et al. 2011; Pronk et al. 2013), and the content of iron oxy-hydroxides (Rasmussen et al. 2006; Wissing et al. 2013). A comprehensive meta-analysis of over 5500 soil profiles by Rasmussen et al. (2018) found that, rather than clay content, other soil physicochemical properties—such as exchangeable calcium in alkaline soils and water-limited climates—explain soil organic matter (SOM) stabilization. Additionally, increased soil moisture availability and acidity, along with Al- and Fe-oxyhydroxides, are strong predictors for SOM stabilization.

Reference soil groups (Figure 4b), based on their genesis trajectories and soil properties, play a crucial role in influencing SOC accumulation following agricultural land abandonment (Guo and Gifford 2002). Soils vary in their ability to store and stabilize organic C due to differences in their biogeochemical properties (Jenny 1941; Brady and Weil 2016). Soils with high clay content, such as Vertisols, primarily protect organic C in soil aggregates, leading to greater SOC accumulation compared to sandy soils like Arenosols, which have low aggregation (Tisdall and Oades 1982; Oades 1984). Cai et al. (2016) found that the ratio of mineral-associated OC (MAOC) to total SOC (TSOC) (MAOC/TSOC) in three land uses followed the following order: grassland < cropland < forest. They also found that Ultisols had the highest MAOC/TSOC ratio, followed by Mollisols. Beside the landscape and vegetation changes as consequence of land use/land cover changes, anthropogenic land use disturbances also affect pedodiversity of the landscape (soil-scape diversity) (Ibáñez and Bockheim 2013). Soil reacts to anthropogenic impacts based on the intensity and duration as well as direction of the impacts (Targulian and Bronnikova 2019). Soil pH also affects SOM decomposition, with neutral to slightly acidic soils generally favoring SOC accumulation (Allison 1973; Bååth 1989). The presence of minerals like iron oxides in Ferralsols or allophane in Andosols can further enhance SOC stabilization through interactions with organic matter (Schwertmann and Cornell 2000; Mikutta et al. 2006). Therefore, understanding pedodiversity and how it reacts to human disturbances is crucial for effective land management and environmental sustainability, as soil properties, nutrient cycling, and ecosystem functions are affected by dominant soil formation processes.

Land attributes like aspect (exposition) affect the amount of solar radiation received by soil surfaces, which in turn influences plant growth and SOC dynamics. The interaction of solar irradiance with slope aspect has ecological implications, shaping local temperatures, moisture levels, and vegetation growth (Dubayah and Rich 1995; Bennie et al. 2006). Aspect generates a series of ecological effects that influence soil microclimates, vegetation cover, and biological activity—factors that are crucial for understanding spatial variations in SOM dynamics (Schmidt et al. 2011). Our GLMM analysis showed significant gains of C for specific aspects (especially South and South-West, Figure 4d). According to McCune and Keon (2002), in the Northern hemisphere, South-facing slopes receive the most solar radiation, followed by East-facing ones, making them warmer and drier. While these conditions favor plant species adapted to heat and drought, they can also limit overall plant productivity due to water stress. In contrast, North-facing slopes receive less solar radiation, resulting in cooler and wetter environments that typically support denser vegetation and higher plant productivity. The observed pattern for aspect-SOC dynamics in abandoned lands across Europe indicates that intermediate radiation in South-west facing slopes and afternoon sunlight in West-facing slopes significantly influence the increase in SOC accumulation after abandonment (Figure 4d).

Climate sets the range of temperature and precipitation conditions, which directly regulate microbial activity and decomposition rates (Jobbágy and Jackson 2000). Vegetation succession, which follows different pathways in different biogeographic regions, affects the quantity and quality of organic matter inputs into the soil (Post and Kwon 2000).

Although our findings highlight considerable potential SOC accumulation in the Mediterranean region and some soil reference groups (Regosols, Cambisols, and Calcisols), careful consideration is needed when extrapolating these trends to other regions of Europe. To make accurate generalizations, it is essential to implement further experimental studies across diverse biogeographic zones, local soil, and climatic conditions, especially in underrepresented regions and environmental gradients identified by our gap analysis. While the primary Mediterranean focus of our meta-data analysis may restrict its direct generalizability across Europe, our insights into key environmental drivers of SOC dynamics (i.e., forest type, previous land use, and soil type) are broadly applicable in the same ecological settings.

4.2 | Mechanisms of SOC Accumulation

SOC consists of different pools with varying mean residence times (MRTs) and resistance to biodegradation (Paul and Clark 1996; Del Galdo et al. 2003); therefore, bulk SOC content is likely not the most responsive parameter following abandonment (Six et al. 2002; DeGryze et al. 2004; Lützow et al. 2006). In terms of turnover times, SOC pools can be classified as follows: (1) labile and easily degradable SOC (nonprotected SOC), such as free particulate organic matter (fPOM), plant residues and microbial debris with short turnover time (1–10 years); (2) occluded SOC within microaggregates (physically protected SOC) with medium turnover time ranging from 10 to 100 years; (3) mineral-associated SOC with silt and clay particles with turnover time between 10 and 100 years; and (4) resilient SOC pool (biochemically recalcitrant SOC) with turnover time > 100 years (DeGryze et al. 2004; Lützow et al. 2006; Six et al. 2002). The fPOM fraction, due to its labile nature, appears to be more responsive to land use change and land disturbances than other SOC pools (Cambardella and Elliott 1993).

Secondary succession on abandoned croplands or grasslands influences the mechanisms of soil C sequestration and accumulation. These mechanisms can be outlined as follows:

4.2.1 | Higher Input of Organic Matter by Forest Vegetation

Forest vegetation contributes substantial organic matter inputs through leaf litter, wood debris, and root biomass, which are rich in lignin material, especially in tree-dominated systems. This material decomposes more slowly than herbaceous vegetation, leading to long-term SOC accumulation (Qin et al. 2024). The diversity and density of forest vegetation further enhance C inputs, particularly in the later stages of succession. Most of our data fall within the range of 1–75 years since abandonment. Future studies should focus on identifying naturally rewilded areas older than 75 years to determine when and where SOC accumulation reaches an asymptote or maximum.

4.2.2 | Improvement of Soil Aggregation and Stabilization of Carbon

The interactions between root and microbial activities promote soil aggregation during forest ecosystem development. Tree roots facilitate the formation of soil aggregates that protect organic C from microbial decomposition through physical shielding. Additionally, the incorporation of root exudates and mycorrhizal fungi into soil aggregates enhances such physical protection of SOC (Dignac et al. 2017). This process is crucial for maintaining SOC over the long time through this physical protection mechanism. In the Central Spanish Pyrenees, although an initial woody encroachment may show temporary decreases in SOC stock due to the slow decomposition of coarse organic inputs, SOC stocks recover and even surpass preabandonment levels with the maturation of forests (Nadal-Romero et al. 2021).

4.2.3 | Slower Decomposition Rates Under Forest Canopy

Typically, forest ecosystems create a microclimate under the canopy where temperature fluctuations are smaller, the soil moisture is higher, and UV radiation is lower. These conditions slow down the decomposition rate of organic matter, which in turn accelerates SOC accumulation (Ma et al. 2020).

4.2.4 | Root Dynamics and Below-Ground Carbon Inputs

Forests possess extensive and deep root systems that play a significant role in belowground C storage. Root turnover and the secretion of organic compounds into the rhizosphere provide a continuous supply of both labile and recalcitrant organic matter to the soil. These inputs contribute to enhancing SOC pools, especially in deeper soil layers (Ma et al. 2020). However, the role of land use change on deep soil C reservoirs remains controversial. According to Fontaine et al. (2007), changes in land use or agricultural practices that increase the distribution of fresh C at depth could stimulate the decomposition of ancient buried C (priming effect; Kuzyakov 2002).

4.2.5 | Microbial Community Composition Changes

Forest ecosystems support diverse microbial communities that are specialized in processing complex organic matter inputs (Bardgett and van der Putten 2014). Fungi, particularly mycorrhizal species, dominate forest soils and play a crucial role in the breaking down of lignin-rich plant residues (Pérez-Izquierdo et al. 2021). This microbial activity ultimately contributes to the transformation of organic inputs into stable forms of SOC (Dignac et al. 2017). Metagenomic studies also showed that succession leads to an increase in fungi/bacteria carbon use efficiency (CUE), accelerating mineral-associated SOC formation (Hu et al. 2025). Panico et al. (2025) demonstrated that fungal community richness, as assessed by eDNA metabarcoding, decreased and evenness increased during secondary succession. In contrast, bacterial diversity, measured using eDNA metabarcoding, peaked at early and intermediate stages. Shifts in fungal community composition included an increase in ectomycorrhizal Basidiomycota linked to topsoil higher SOC, N, and C:N ratio. Similarly, Zhou et al. (2023) found that microbial biomass and enzyme activities increase following cropland abandonment, shifting SOC fractions from labile to more stable pools, demonstrating the key role of microbial community in SOC stabilization.

4.2.6 | Less Soil Disturbance

After abandonment, soils experience minimal disturbance, allowing organic matter to accumulate over time. The absence of plowing or grazing ensures that the SOC pool is both preserved and enhanced through natural processes (Qin et al. 2024). Additionally, forests exhibit lower soil erosion rates compared to croplands, which further promotes higher SOC accumulation over time (Panagos et al. 2015).

The underlying mechanisms for SOC formation typically include increased organic matter inputs, improved aggregation, reduced decomposition rates, extensive rooting, and shifts in microbial community composition, particularly, during the transition from croplands to forest vegetation. These processes enhance SOC accumulation, leading to long-term stabilization and offering significant potential for C sequestration in naturally reforested landscapes. Schneider et al. (2024) also suggested the key role of vegetation density in enhancing SOC sequestration on abandoned cultivated terraces in northern Spain. They found that dense natural vegetation significantly facilitates SOC recovery compared to the sparsely covered areas.

4.3 | Conclusions and Future Research Directions

This work highlights the significant potential of natural vegetation recovery of abandoned agricultural lands in Europe to enhance SOC sequestration, thereby contributing to climate change mitigation. Our synthesis of 36 relevant studies shows that previous cropland areas that have grown into mixed and broadleaf forests exhibit a pattern of SOC accumulation over time, thus helping in overall carbon sequestration over time. We would like to note that this finding should not be interpreted as a general recommendation for widespread cropland abandonment. Land-use decisions involve multiple ecological, economic, and societal considerations that extend beyond carbon storage alone.

In contrast, the response of previous grassland areas is more variable and lacks a substantial upward trend. While previous studies have primarily focused on Mediterranean regions, there is a need for broader research in understudied areas such as the Atlantic, Boreal, and Pannonian regions. The gap analysis identifies key areas in Europe where future research should focus on improving our understanding of the environmental and ecological factors influencing SOC dynamics. Based on the findings and identified gaps in the current study, future research needs to focus on the following three critical directions:

i. Long-term SOC dynamics
   a. Implementing long-term experiments (> 10 years) via permanent plots or investigating more chronosequences to reveal changes in SOC sequestration rates following the secondary succession. This provides insights into the long-term SOC trends in rewilded ecosystems.
   b. Characterizing SOC pools (i.e., labile, occluded, and mineral-associated SOC) to understand their changes and contribution to postabandonment SOC stabilization.

ii. Mechanisms of SOC stabilization
   a. Investigating soil microbial community contribution and key taxa in post-abandonment SOC dynamics.
   b. Evaluating the influence of litter quality from different forest trees on SOC dynamics in rewilded ecosystems.

iii. Regional and climatic gradients
   a. Prioritizing research in underrepresented biogeographic zones such as Atlantic, Boreal, and Pannonian regions to achieve deep understanding of regional SOC dynamics in abandoned croplands and grasslands.
   b. Implementing comparative studies across climatic and environmental gradients to investigate how temperature, precipitation, soil type, slope, and aspect affect succession and SOC dynamics.

These detailed directions aim to address the existing gaps in knowledge and methodology in SOC research on abandoned agricultural lands. By focusing on long-term trends, underrepresented regions, and advanced technologies, these efforts will significantly contribute to a deeper understanding of soil carbon dynamics and their role in climate mitigation strategies.

Author Contributions

Mohammad Tahsin Karimi Nezhad: conceptualization, writing – original draft, methodology, visualization, writing – review and editing, software, formal analysis, data curation, resources. **Domagoj Gajski:** methodology, visualization, writing – review and editing, software, formal analysis, resources. **Clara G. Jeanroy:** visualization, software. **Peter H. Verburg:** investigation, writing – review and editing, project administration, supervision. **Giorgio Alberti:** conceptualization, funding acquisition, writing – review and editing, project administration, supervision. **Pavel Šamonil:** conceptualization, funding acquisition, validation, writing – review and editing, project administration, supervision.

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Data Availability Statement

The data that support the findings of this study are available in https://doi.org/10.5281/zenodo.20132630.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** gap_analysis_script. **Data S2:** meta_analysis_script. **FIGURE S1:** Relationship between different levels of categorical variables is displayed through stack bar plots. Only levels with more than 10 observations from multiple studies are shown here. **FIGURE S2:** The histogram shows the number of cell grids with a specific percentage of relative cropland abandonment. The red dashed line represents the threshold used to identify large areas (greater than 10% of the cell grid, i.e., larger than 10 hectares) analyzed in the gap analysis. Although these larger areas appear in smaller quantities on the histogram, they still account for more than 70% of the abandoned cropland surface area between 2000 and 2018. **FIGURE S3:** The histogram shows the number of cell grids with a specific percentage of relative grassland abandonment. The red dashed line represents the threshold used to identify large areas (greater than 10% of the cell grid, i.e., larger than 10 hectares) analyzed in the gap analysis. Although these larger areas appear in smaller quantities on the histogram, they still account for more than 67% of the abandoned cropland surface area between 2000 and 2018. **FIGURE S4:** The probability of lacking SOC data necessary for a comprehensive overview of SOC change over time since cropland abandonment across Europe was calculated across five environmental gradients: average annual temperature, average annual precipitation (log scaled), elevation (log scaled), soil pH, and cation exchange capacity. The distribution of abandoned croplands collected from literature is represented at the 0 point on the y-axis, while newly abandoned croplands obtained from Corine land cover raster layers between 2000 and 2018 are at the 1 point on the y-axis. The red line shows the predicted non-linear probability of lacking data for areas along the environmental gradient, based on the full distribution of the environmental gradient across Europe. This prediction trend line was generated using a Generalized Additive Model (GAM) with a quasibinomial error structure (GAM-qb). **FIGURE S5:** The probability of lacking SOC data necessary for a comprehensive overview of SOC change over time since **grassland** abandonment across Europe was calculated across five environmental gradients: average annual temperature, average annual precipitation (log scaled), elevation (log scaled), soil pH, and cation exchange capacity. The distribution of abandoned croplands collected from literature is represented at the 0 point on the y-axis, while newly abandoned croplands obtained from Corine land cover raster layers between 2000 and 2018 are at the 1 point on the y-axis. The red line shows the predicted non-linear probability of lacking data for areas along the environmental gradient, based on the full distribution of the environmental gradient across Europe. The prediction trend line was generated using a Generalized Additive Model (GAM) with a quasibinomial error structure (GAM-qb). **FIGURE S6:** A map of Europe displays the areas of abandoned **croplands** that were abandoned between 2000 and 2018. Each dot represents an abandoned area, with color indicating its importance as a future sampling site. The importance level was determined based on the 98.5% probability threshold of missing data for one to five environmental gradients (mean annual precipitation, mean annual temperature, elevation, soil pH, or cation exchange capacity). The importance level increases depending on the number of gradients for which data is lacking. The dots on the map have been enlarged for better visualization and do not reflect the original sizes of the 1 km^2 patches of abandoned areas extracted from the Corine land cover rasters. **FIGURE S7:** A map of Europe highlights areas of abandoned **croplands** that were abandoned between 2000 and 2018. Each dot represents an abandoned area, colored according to its importance as a future sampling site. The importance level was determined based on the 99.5% probability threshold of missing data for one to five environmental gradients (mean annual precipitation, mean annual temperature, elevation, soil pH, or cation exchange capacity). The importance level increases depending on the number of gradients for which data is lacking. The dots on the map have been enlarged for better visualization and do not represent the original sizes of the 1 km^2 patches of abandoned areas extracted from the Corine land cover rasters. **FIGURE S8:** A map of Europe displays the areas of abandoned **grasslands** that were abandoned between 2000 and 2018. Each dot represents an abandoned area, with color indicating its importance as a future sampling site. The importance level was determined based on the 98.5% probability threshold of missing data for one to five environmental gradients (mean annual precipitation, mean annual temperature, elevation, soil pH, or cation exchange capacity). The importance level increases depending on the number of gradients for which data is lacking. The dots on the map have been enlarged for better visualization and do not reflect the original sizes of the 1 km^2 patches of abandoned areas extracted from the Corine land cover rasters. **FIGURE S9:** A map of Europe highlights areas of abandoned grasslands that were abandoned between 2000 and 2018. Each dot represents an abandoned area, colored according to its importance as a future sampling site. The importance level was determined based on the 99.5% probability threshold of missing data for one to five environmental gradients (mean annual precipitation, mean annual temperature, elevation, soil pH, or cation exchange capacity). The importance level increases depending on the number of gradients for which data is lacking. The dots on the map have been enlarged for better visualization and do not represent the original sizes of the 1 km^2 patches of abandoned areas extracted from the Corine land cover rasters. **FIGURE S10:** Distribution of sampling sites based on the time since the abandonment of agricultural areas. **TABLE S1**. List of considered papers.