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Research Paper

# Cropping history, agronomic rules, and commodity prices shape crop rotations across Central Europe

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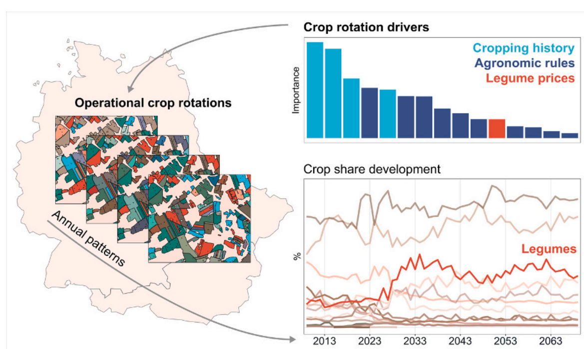
## HIGHLIGHTS

- This study identifies drivers that determine operational crop rotation practices.
- Past cropping, agronomic recommendations, and legume prices shape crop rotations.
- The analysis is based on over 16 million field records over Central Europe.
- Rotation projections at field level reflect farmers' uncertain decision-making.
- The importance of legume cropping is expected to increase in the future.

## GRAPHICAL ABSTRACT

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## ABSTRACT

*Context:* Crop rotations provide agronomic benefits over monocropping, such as enhanced nitrogen supply, improved weed and pest control, and higher yields. Although the theoretical understanding of optimal rotations has advanced, little is known about their real-world implementation and the factors influencing rotation decisions on large scales.
*Objective:* Understanding these factors is key for projecting future cropping patterns, refining agricultural policy, and improving crop models that often oversimplify rotation practices. This study identifies the drivers influencing operational crop rotations across Central Europe and projects future cropping patterns in the region.
*Methods:* We analyse over 16 million field-year combinations from Germany, Austria, and the Czech Republic. Using a random forest algorithm, we determine feature importance and apply a novel machine learning approach

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that incorporates uncertainty in farmers' decision-making to provide a potential outlook on cropping patterns until 2070.
*Results and Conclusions:* Historical cropping patterns, agronomic practices, and legume commodity prices significantly shaped crop rotations across the region. Projections indicate a substantial increase in legume cultivation over the coming decades, with implications for nitrogen budgets, dietary transitions, and in-silico upscaling.
*Significance:* Rather than optimizing rotations, this study identifies key drivers of operational crop rotations in Central Europe. The findings provide the basis for large-scale simulations that represent cropping patterns more realistically. To the best of our knowledge, the data set compiled here is the most extensive yet analysed in the context of operational crop rotation management.

## 1. Introduction

Growing different crops in a repeating sequence on the same field – frequently referred to as crop rotation – is an agricultural practice that has been used for thousands of years (Yates, 1954; Bogaard et al., 1999). Crop rotations have various benefits over monocropping, including an increase in nitrogen supply to crops (Watson et al., 2002; Reckling et al., 2016; Notz et al., 2023), improved control of weeds (Bàrberi, 2002), and soil-borne pests and diseases (Vereijken, 1997; Zinati, 2002), enhanced resource use efficiency (Bachinger and Stein-Bachinger, 2000), and in summary, an increase in crop yield overall (Bullock, 1992; Barbieri et al., 2019; Reckling et al., 2022). High-level stakeholders, such as the Intergovernmental Panel on Climate Change (IPCC, 2022) and the Food and Agriculture Organization of the United Nations (FAO, 2022), therefore emphasise the importance and benefits of diversified crop rotations in the context of climate change adaptation and mitigation.

The agronomic theory behind designing optimal crop rotations is well established and planning tools are widely available (Bachinger and Zander, 2007; Schönhart et al., 2011; Pahmeyer et al., 2021). Best practice rotations often include cultivation breaks of six to seven years between the same crop for phytosanitary reasons (Jeangros and Courvoisier, 2019), or a higher proportion of legumes (Hufnagel et al., 2020; Reckling et al., 2022) for biological nitrogen fixation or as green manure. These optimal approaches are based on logical rules and best practice examples, but the implementation of real-world crop rotations may not follow these approaches exclusively. Environmental conditions, farmers' individual cultivation preferences, market price incentives (e.g. for oilseeds from production depressions in Ukraine (agrarheute, 2022; Bloomberg, 2022), and agro-political decisions can change cropping frequencies and thus crop rotations operationally. Such opportunistic decisions, and more generally, factors other than best practice approaches or stylised sequences have rarely) been taken into account when analysing crop rotation patterns. Stein and Steinmann (2018) focused the importance of socioeconomic factors for shaping less diverse crop rotation types in Germany in the recent past. Dupuis et al. (2023) and Upcott et al. (2023) used cropping habits to predict crop rotations in Canada and the UK, respectively. And Revoyron et al. (2022) showed that agronomic, economic or work-related factors motivate or hinder crop diversification. Beyond this, a joint analysis of environmental, agronomic, economic, and political drivers and cropping habits to understand and project space- and time-specific cropping decisions has been missing so far. The research question of this study therefore was which of the above drivers shape operational crop rotations at large spatial coverage, and how the respective dynamic could translate into future cropping practices across the study region.

Advancing the present understanding of "real-world" rotational cropping would be crucially important, especially for the following two aspects. Firstly, in the context of climate change adaptation and mitigation, the benefits of diversified crop rotations have received increasing political attention from high-level institutions such as the Intergovernmental Panel on Climate Change (IPCC, 2022) and the Food and Agriculture Organization of the United Nations. And in the European Union (EU), subsidy payments for diversification measures have long been part of the Common Agricultural Policy (CAP) (EU, 2022; Galioto and Nino, 2023). Understanding the drivers that shape crop rotations would provide a means to assess agro-political measure efficacy and a lever for designing such measures to promote crop diversification goals. And secondly, crop and bio-economic modelling studies, which scale up farming practices and also inform integrated assessments and policy decisions, mostly ignore crop rotations or use simplified practices for their simulations, commonly assuming monocropping across all agricultural land and over the time period of interest. Some studies have started to put individual crops in the context of their rotation but still use stylised assumptions or best practice examples (Stella et al., 2019; Faye et al., 2023; Nendel et al., 2023; Kik et al., 2024). The fact that operational cropping patterns may look very different from optimised rotations, and that they may also change over time, has not been considered in this context yet. To better account for the multiple benefits of rotations when scaled up in-silico, an understanding and representation of related drivers, and a projection of real-world conditions based on this understanding is therefore urgently needed (Basso et al., 2015; Kollas et al., 2015; Teixeira et al., 2015; Pohanková et al., 2024; Timlin et al., 2024).

As outlined earlier, relying on traditional tools for designing optimal rotations based on fixed agronomic rules may not capture the reality of operational crop rotation decisions. Machine learning (ML), on the other hand, can extract practical rules and identify key drivers from real-world observational data of past cropping patterns (Ryo and Rillig, 2017). Previous studies have demonstrated the potential of using ML to classify rotations in Great Britain (Upcott et al., 2023) or to predict the next crop in a rotation in France (Osman et al., 2015).

While these studies focused on pattern recognition, the aim of the present study was to identify drivers for operational crop rotation management across multiple countries in central Europe (Germany, Austria, and the Czech Republic). To the best of our knowledge, this study provides the most extensive analysis of operational crop rotation management so far, especially considering more than one country.

We analysed over 16 million operational field-year records and hypothesised that rotational decisions are based on:

- field-specific cropping history and neighbouring rotations (section 2.1.1)
- agronomic rules for good rotation practice (section 2.1.2)
- prevailing environmental conditions (section 2.1.3)
- crop commodity prices (section 2.1.4), and
- agricultural policies and subsidy measures (section 2.1.5).

We used a random forest (RF), a powerful bot not overly complex ML algorithm (Liakos et al., 2018; Ryo, 2022) that solves classification problems based on majority votes from an ensemble of decision trees and has been used for crop type identification before (Blickensdörfer et al., 2022). We applied spatio-temporal cross-validation and forward feature selection (Meyer et al., 2018; Meyer et al., 2019) considering uncertainties inherent in farmers' decision-making and -based on that- generated a potential outlook on cropping developments until 2070.

## 2. Methods

### 2.1. Data sets and respective features

In the following, we describe different data sets and related features that provided the necessary basis for our analysis. Table 3 gives a comprehensive overview of all features included. A summary of links to all publicly available data sets can be found in the Data availability section at the end of the manuscript.

#### 2.1.1. Field-level rotation records

We used data from the Geo-spatial Application (GSA) (Leonhardt et al., 2024) of the EU's Integrated Administration and Control System (IACS) (Tóth and Kučas, 2016) across Germany, Austria, and the Czech Republic (Fig. 1).

The IACS data lists all agricultural fields for which farmers have applied for CAP subsidies, containing (at least) the location and size of the field, and the main crop of the respective year in shapefile format (the availability of additional information differs between regions and years). For this study, we had access to IACS data from nine German federal states (Bavaria, Brandenburg, Lower Saxony, Mecklenburg-Western Pomerania, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Saxony, and Thuringia; 13,589,421 field-year combinations in total), Austria (2,384,993 field-years), and the Czech Republic (167,957 field-years). Table 1 provides an overview of their regional availability. Non-publicly available data sets were retrieved through bilateral, project-based exchange with responsible officers at the providing institution.

To aggregate the data from individual years and states to a full set of sequential cropping information for distinctly identifiable fields over the entire study domain, we had to overcome the challenge that the shape and number of fields in the original IACS data potentially change from one year to the next. Jänicke et al. (2022) applied an area-based fitting to address such interannual discrepancies. As we did not consider field size for this study, we instead (i) calculated the centroid for each field in the latest available year of each state (see Table 1), (ii) extracted CTypes from all previous years that overlapped with these centroids, and (iii) assigned a unique identifier for each individual field after combining all years per field and all fields across each state into one data set. Although the original IACS data includes a field identifier, this index only considers fields within a state and a small percentage of fields are duplicated or overlap close to borders.

Crop descriptions vary between regions and between years within a region. Therefore, we harmonised all crop descriptions into 17 crop types (CType, Table 2), as used in previous studies (Blickensdörfer et al.,

**Table 1**
Overview of the IACS data sets included in this study. Publicly available data sets are marked with (*). Respective links can be found in the Data availability section at the end of the manuscript.

| State | Available years | Provider |
|---|---|---|
| Austria (*) | 2015–2023 | Agrarmarkt Austria (2025) |
| Brandenburg (*) | 2005–2023 | Ministerium für Land- und Ernährungswirtschaft, Umwelt und Verbraucherschutz (2024) |
| Bavaria | 2005–2023 | Bayerisches Staatsministerium für Ernährung, Landwirtschaft, Forsten und Tourismus |
| Czech Republic (*) | 2019–2023 | Ministerstvo zemědělství České republiky (2025) |
| Lower Saxony (*) | 2009–2023 | ML/SLA Niedersachsen (2025) |
| Mecklenburg-Western Pomerania | 2016–2023 | Ministerium für Landwirtschaft und Umwelt |
| North Rhine-Westphalia (*) | 2019–2023 | Landwirtschaftskammer Nordrhein-Westfalen (2025) |
| Rhineland-Palatinate | 2005–2021 | Ministerium für Wirtschaft, Verkehr, Landwirtschaft und Weinbau |
| Saarland | 2012–2023 | Landesamt für Vermessung, Geoinformation und Landentwicklung |
| Saxony | 2015–2023 | Sächsisches Staatsministerium für Energie, Klimaschutz, Umwelt und Landwirtschaft |
| Thuringia | 2010–2014 | Thüringer Landesamt für Landwirtschaft und Ländlichen Raum |

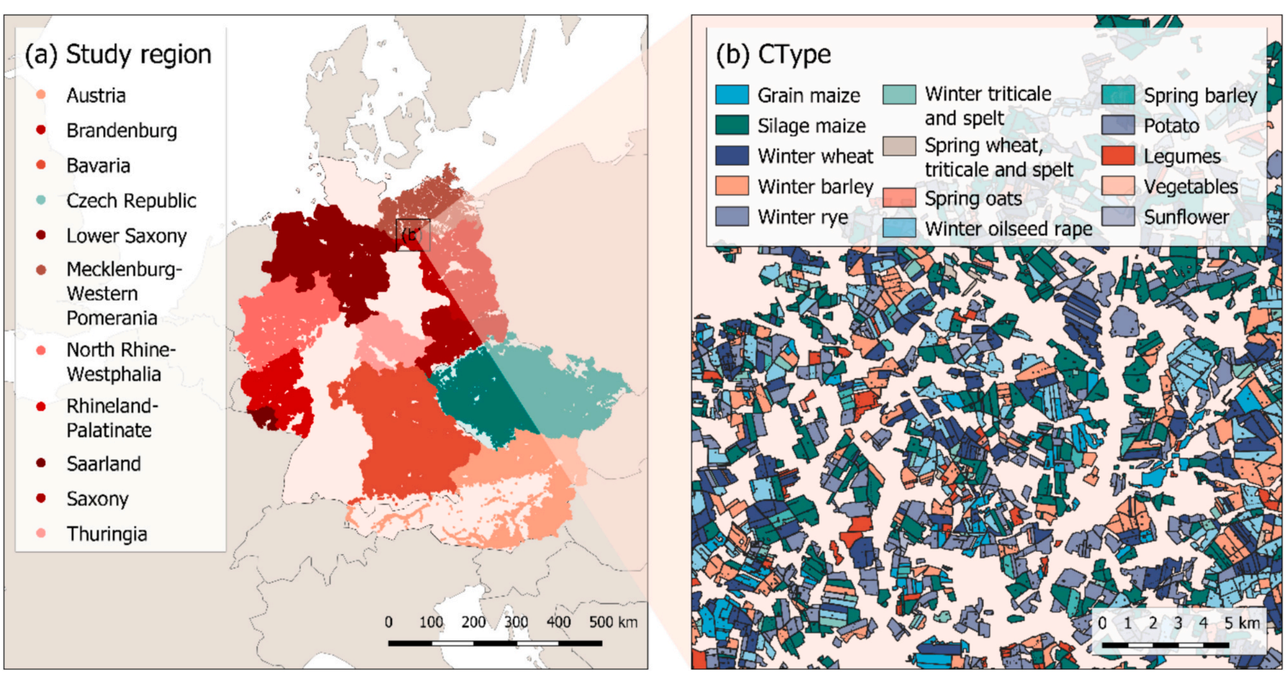


**Fig. 1.** Study regions. The shaded points show all the fields in nine German federal states, Austria, and the Czech Republic that were used to train and test the crop rotation model. Germany and Austria in shades of red show the training area for the alternative model, excluding all features selected for the first model. (b) IACS data showing the diversity of crop types using the example of the German state of Brandenburg in 2023. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2022; Jänicke et al., 2022). With the focus on crop rotations, we excluded permanent grassland (12 %), and fields with perennial crops (e.g. orchards or vineyards), speciality crops (e.g., herbs or ornamental flowers), or crops not part of the 17 CTypes (36 % for all of the latter three) beforehand. To avoid giving any hints about the current CType (known as the “data leakage” problem), we considered the current CType for each field and year ($CType_y$, y = 2009:2023 (y = 2005:2008 appear as $PCType_i$ (see next) for y = 2009)) as the dependent variable only. Instead, we used CType of the four previous years ($PCType_i$, $i$ = 1:4) and the most common $PCType_i$ within a radius of 5 km ($NPCType_i$, i = 1:4) as predictive features. The $NPCType_i$ serves as a proxy for neighbouring crop rotations.

### 2.1.2. *Agronomic rules*

Best practice guidelines for optimal crop rotations are extensive (Bachinger and Zander, 2007; Schönhart et al., 2011; Pahmeyer et al., 2021; Fenz et al., 2023a). For practical reasons and operational relevance with regional context, we included agronomic rules from Jeangros and Courvoisier, 2019 and the Landwirtschaftskammer Nordrhein-Westfalen (2015). We assigned the following features to each $PCType_i$ (see Table 2 for a crop-specific overview):

- Winter vs. spring crop: a binary “Yes” or “No” feature according to the sowing time
- Cereal vs. leafy crops: a binary “Yes” or “No” feature, depending on whether the crop is gramineous or not
- Nutritional demand: classified as “Low”, “Medium”, or “High”, depending on the respective demand for nutrients (Jeangros and Courvoisier (2019) and Landwirtschaftskammer Nordrhein-Westfalen (2015))
- Organ: classified as “Grain”, “Biomass”, or “Root”, depending on the respective organ for primary yield
- Drought tolerance: classified as “Low”, “Medium”, or “High”, depending on the respective drought tolerance (Jeangros and Courvoisier (2019)
- Fraction: indicates the recommended maximum cultivation fraction of each crop in the rotation. A value of 1 would refer to unproblematic monocropping. The smaller the value the longer the recommended cultivation break (Jeangros and Courvoisier (2019) and Landwirtschaftskammer Nordrhein-Westfalen (2015)).

Following the methodology described by Stein and Steinmann (2018) and Jänicke et al. (2022), we further assigned each field-year to a category of structural (struc) and functional (func) diversity. Struc is the ratio of transitions (*Tr*, the number of CType changes) to the number of crops (Cn), and categories of func are derived from the leafy-to-cereal (*LC*) and the winter-to-spring (*WS*) crop ratio per field. The former can be interpreted as a measure for agricultural intensification, while the latter has been reported to be beneficial for interrupting the accumulation of weed communities, pests, and diseases.

Stein and Steinmann (2018) originally used their typology to classify seven-year crop rotations, which was not applicable to most fields included in this study. Therefore, we had to adjust the classification of *Tr* into “High”, “Middle” and “Low” (Eq. 1), and the calculation of *LC* (Eq. 2) and *WS* (Eq. 3) depending on the availability of IACS data for each country ($n$, Germany: 19 (2005–2023), Austria: 9 (2015–2023), and Czech Republic: 5 (2019–2023)). For classifying *Tr*, we used their original numbers (High: 5–6, Middle: 3–4, Low: 1–2) and multiplied it with the ratio ($l$) between $n$ and Stein and Steinmann’s (2018) seven-year rotation length.

$$Tr = \begin{cases} High, & (5*l) \leq Tr \\ Middle, & (3*l) \leq Tr < (5*l) \\ Low, & (1*l) \leq Tr < (3*l) \end{cases} \tag{1}$$

**Table 2**
Overview of crop types (CType) used to group the original crop descriptions from the from the Geo-spatial Application (GSA) data of the EU’s Integrated Administration and Control System (IACS) in the study region, and the corresponding agronomic features (Winter: winter vs. spring crop, Cereal: cereal vs. non-cereal crop, Demand: nutritional demand (Jeangros and Courvoisier (2019) and Landwirtschaftskammer Nordrhein-Westfalen (2015)), Organ: crop organ for primary yield, Drought: drought tolerance (Jeangros and Courvoisier (2019), Fraction: recommended maximum fraction of each crop in the rotation (1 = unproblematic monocropping; the smaller the value the longer cultivation breaks are recommended, Jeangros and Courvoisier (2019) and Landwirtschaftskammer Nordrhein-Westfalen (2015))).

| CType | Notes | Winter | Cereal | Demand | Organ | Drought | Fraction |
|---|---|---|---|---|---|---|---|
| Grain maize (MG) | | No | Yes | High | Grain | Low | 0.4 |
| Silage maize (MS) | Includes sorghum | No | Yes | High | Biomass | Low | 0.4 |
| Winter wheat (WW) | | Yes | Yes | Medium | Grain | Medium | 0.5 |
| Winter barley (WB) | | Yes | Yes | Medium | Grain | High | 0.66 |
| Winter rye (WR) | | Yes | Yes | Medium | Grain | High | 0.66 |
| Winter triticale and spelt (WTS) | | Yes | Yes | Medium | Grain | Medium | 0.5 |
| Spring wheat, triticale, and spelt (SWTS) | | No | Yes | Medium | Grain | Low | 0.5 |
| Spring barley (SB) | | No | Yes | Medium | Grain | Low | 0.66 |
| Spring oat (SO) | | No | Yes | Medium | Grain | Low | 0.25 |
| Winter oilseed rape (WOR) | Includes other brassicas | Yes | No | High | Grain | Medium | 0.25 |
| Sugar beet (SU) | Includes other beets | No | No | High | Root | Medium | 0.25 |
| Potato (PO) | | No | No | High | Root | Low | 0.25 |
| Legumes (LEG) | Includes peas, beans, lupin, soybean, lentil, chickpea, lucerne, clover, and other legumes | No | No | Low | Grain | Medium | 0.23 |
| Other leafy vegetables (VEG) | | No | No | High | Grain | Low | 0.25 |
| Sunflower (SUN) | | No | No | High | Grain | Low | 0.25 |
| Onion (ON) | | No | No | Low | Root | Low | 0.43 |
| Carrot (CA) | | No | No | Medium | Root | Low | 0.43 |

$$LC = \frac{1}{n-1}\sum CType > 9 \tag{2}$$

$$WS = \frac{1}{n-1}\sum CType \in \{1,2,7,8,9,11,\ldots,19\} \tag{3}$$

We included the same number of CTypes. Therefore, Cn remained unchanged and struc was classified according to Cn and the adjusted *Tr* values. The classification of func in principle also remained the same, based on the relative *LC* and *WS* values, however. For a graphical representation of the general struc and func matrices, we refer to Fig. 2 in Stein and Steinmann (2018).

#### 2.1.3. Environmental conditions

We obtained elevation and slope data from the German (Bundesamt für Kartographie und Geodäsie, 2016)/Austrian (geoland.at, 2015) Digital Terrain Model DGM10 (10 m resolution). We extracted the organic carbon content (Corg) of the first soil layer and the sand, silt, and clay content of the second soil layer from the German land use-specific soil map (based on Bundesanstalt für Geowissenschaften und Rohstoffe (2008), 100 m resolution). For Austria, we used the digital soil map (Bundesforschungs- und Ausbildungszentrum für Wald, Naturgefahren und Landschaft, 2023), 1 km resolution), which only provides values for the full profile. We retrieved the humus, sand, silt, and clay contents and divided the original values by 1.725 (converting humus to Corg) and 100 (sand, silt, clay) to match the units of the German soil data.

We used daily temperature and precipitation data from 1 km gridded products from the German Weather Service (Deutscher Wetterdienst, 2024) and GeoSphere Austria (2025). To mimic the "climate memory" of farmers', which we assumed to cover the last five years, we aggregated daily values to monthly averages and calculated monthly averages from the previous five years over three major growth periods: March to August (TempMA and PrecMA), April to May (TempAM and PrecAM), and June to July (TempJJ and PrecJJ).

To address the complexity of the environmental conditions while simplifying their magnitude, we used an unsupervised K-means ($n = 25$) clustering approach via Principal Component Analysis (PCA), covering 89.9 % of the observed environmental variance. We assigned each field-year to the cluster based on the five most important PCs, which reduced the number of related features from 12 (elevation, slope, Corg, sand, silt, clay, TempMA, TempAM, TempJJ, PrecMA, PrecAM, and PrecJJ) to one (the respective cluster) and facilitated efficient model training.

#### 2.1.4. Commodity prices

In line with the climate memory of farmers, we calculated the average price of the previous five years for each CType and year (average) from FAOSTAT producer prices (FAO, 2025). We also calculated the difference between averageP and last year's CType price as a short-term economic stimulus (deltaP). In case price data was not available for a specific year, we used prices from the last available year. No legume (LEG) prices were available for the Czech Republic. We therefore used prices for Austria instead. We only used last year's price to avoid any kind of data leakage. Producer prices are usually set after the harvest and are therefore not available to farmers at the time of decision (= planting). Further, we excluded prices for silage maize as it is largely grown as a fodder or energy crop without official market prices.

To generate an outlook on potential cropping patterns in the future, we used commodity price developments from the global biosphere management model (GLOBIOM) (Havlík et al., 2014; Ermolieva et al., 2015). GLOBIOM is a partial equilibrium model that represents global agricultural markets by overall welfare maximisation at regional and global levels. The model integrates a detailed representation of land-use, agricultural market, and productivity changes to assess their impact on prices. Key drivers such as climate change, population growth, dietary shifts, and bioenergy demand influence long-term price trends. Commodity prices fluctuate due to global supply and demand interactions, production costs, and trade dynamics, acting as a feedback mechanism that shapes producer and consumer behaviour.

To calculate average_LEG and deltaP_LEG (as features required to apply the crop rotation model, see Results) we further made the following assumptions. We considered projected prices only for soybean and peas. While FAOSTAT also reports prices for chickpeas and beans, these correspond to post-harvest dried products, resulting in prices up to 10 times higher than those of soybean and peas, which exclude post-processing. GLOBIOM prices for different emissions scenarios deviated by $+-0.5$ USD tonne$^{-1}$ over the projection period only. Therefore, we did not run scenario-specific projections but calculated the average price development overall. Further, as GLOBIOM provides decadal price development, we interpolated the prices between two consecutive decades through a linear fit to retrieve annual values.

Table S. 1 to Table S. 3 in the Supplementary Material provide summarises of price data used for this study.

#### 2.1.5. Agricultural policies and subsidies

To reflect the effect of agricultural subsidies or other policy measures on cropping decisions, we included a "Positive", "Negative", or "None" feature for each field-year, depending on whether any of the following measures were in place or not, and whether they encouraged or discouraged the cultivation certain crops (listed chronologically):

- Energy crop premium ("ECP", Energiepflanzenprämie): effective in Germany from 2003 to 2009, providing subsidies for energy crops (e.g. silage maize)
- Renewable Energy Sources Act ("REL", Erneuerbare-Energien-Gesetz 2014): effective in Germany until 2014, providing additional subsidies for energy crops
- Protein crop promotion strategy ("PCP", Eiweißpflanzenstrategie): effective in Germany from 2014 and in Austria from 2020, promoting the cultivation of legumes at the policy level
- Ban on the use of seed treatments ("BST", Beizverbot): effective from 2014
- Greening: effective during the CAP period from 2014 to 2022, where legumes qualified as ecological priority areas, which are compulsory for subsidy payments
- Diversification of crop production ("DCP"): effective during the CAP period from 2014 to 2022 on top of Greening measures (see previous) in nine German federal states (*Bavaria*, Baden-Württemberg, Hesse, *Mecklenburg-Western Pomerania, North Rhine-Westphalia, Rhineland-Palatinate*, Saxony-Anhalt, Schleswig-Holstein, and *Thuringia*; the federal states relevant for this study are marked in italics). DCP provides subsidies if crop production at farm level includes a minimum of 10 % legumes and a maximum of 65 % cereals. DCP also includes crop rotation and crop diversification measures as part of the conditionality of the most recent CAP period (2023-2027), which is only relevant to the last year of IACS data used for this study, however.
- Abolition of sugar quota ("ESQ", Wegfall der Zuckerquote): effective from 2017
- Ban on the use of neonicotinoids ("BNN"): effective from 2019

### 2.2. Model training

We used a random forest (RF) ML algorithm (Breiman, 2001) and trained it to predict the CType for each field-year combination using the features listed in Table 3, with the exception of "OBJECTID", to be transferable to other fields.

The difficulty with the present data set was its inherent spatio-temporal dependencies. For machine learning problems, this commonly leads to overfitted models that are hardly able to make predictions beyond the location and time considered in the reference data, as well as an overly optimistic error assessment (Meyer and Pebesma,

**Table 3**
Overview of all features.

| Feature | Description | Value | | Notes |
|---|---|---|---|---|
| General | | | | |
| OBJECTID | Unique identifier for each field included in the dataset | 1–15,811,713 | | |
| State | IACS data was available for the nine German federal states, Austria, and the Czech Republic | BV, BB, LS, MWP, NRW, RP, SA, SAX, TH, AT, CZ | | |
| Year | Current cropping year | 2005 (earliest) – 2023 (latest) | | For each state, the first four years were included via $PCType_i$ only |
| Cropping history | | | | |
| CType | The crop type grown in each year | | | CType is the dependent variable |
| $PCType_i$ | The crop type grown i years ago | | | See Table 2 for a description of the CType |
| $NPCType_i$ | The most common $PCType_i$ type within a radius of 5 km | | | i = 1,2,3,4 |
| Environmental conditions | | | | |
| Cluster | The growing environmental cluster,<br>based on the following growing conditions: | 1–25 | | |
| | | 10th Percentile | Median | 90th Percentile |
| Elev | The elevation of each field (m a.s.l.) | 0.0 | 372.5 | 469.3 |
| Slope | The slope of each field (%) | 0.0 | 4.6 | 7.5 |
| Sand | The sand content of each field's soil (%) | 1.0 | 30.0 | 60.0 |
| Silt | The silt content of each field's soil (%) | 1.0 | 40.0 | 58.0 |
| Clay | The clay content of each field's soil (%) | 0.0 | 21.0 | 30.0 |
| Corg | The organic carbon content of each field's soil (%) | 0.0 | 1.7 | 1.7 |
| TempMA | Average temperature from March to August over the last five years (°C) | 12.8 | 13.4 | 14.9 |
| TempAM | Average temperature from April to May over the last five years (°C) | 8.4 | 9.1 | 10.5 |
| TempJJ | Average temperature from June to July over the last five years (°C) | 11.9 | 12.5 | 14.0 |
| PrecMA | Average monthly precipitation from March to August over the last five years (mm) | 54.4 | 67.8 | 90.8 |
| PrecAM | Average monthly precipitation from April to May over the last five years (mm) | 41.2 | 54.7 | 75.0 |
| PrecJJ | Average monthly precipitation from June to July over the last five years (mm) | 51.8 | 64.7 | 87.4 |
| Agronomic rules (see Table 2 for crop-specific classification) | | | | |
| $Winter\_PCType_i$ | Differentiation between winter vs. spring crops | Yes/No | | |
| $Cereal\_PCType_i$ | Differentiation between cereal and leafy crops | Yes/No | | |
| $Demand\_ PCType_i$ | Nutritional demand | Low/Medium/High | | |
| $Organ\_ PCType_i$ | Organ for primary yield | Grain/Biomass/Root | | |
| $Drought\_ PCType_i$ | Drought tolerance | Low/Medium/High | | |
| $Fraction\_ PCType_i$ | The recommended cultivation fraction of $PCType_i$ in a rotation | 0–1 | | |
| Struc | The structural diversity of each field | A-I | | See Stein and Steinmann (2018) |
| Func | The functional diversity of each field | 1–9 | | |
| Prices | | | | |
| averageP_CType | The five-year average producer price of CType | | | For details see Table S. 1 to Table S. 3 in the Supplementary Material |
| deltaP_CType | The difference between the averageP_CType and last year's CType price | | | |
| Policies and subsidies | | | | |
| ECP | Energy crop premium | Positive/Negative/None | | Only for Germany |
| REL | Renewable Energy Sources Act | Positive/Negative/None | | Only for Germany |
| PCP | Protein crop promotion | Positive/Negative/None | | |
| BST | Ban on the use of seed treatments | Positive/Negative/None | | |
| Greening | CAP 2014–2022 greening measures | Positive/Negative/None | | |
| DCP | Diversification of crop production | Positive/Negative/None | | Only for some German states |
| ESQ | Abolition of sugar quota | Positive/Negative/None | | |
| BNN | Ban on the use of neonicotinoids | Positive/Negative/None | | |

2021; Meyer et al., 2018; Meyer et al., 2019). To overcome this, we applied a three-step model training:

1. For a first exploratory analysis, we ran a rf model from the R caret package (Kuhn, 2008) with a random split between 80 % and 20 % of all data from Germany and Austria (where all environmental features were available) for training and testing. As described, this led to substantial overfitting.
2. To overcome this, we continued with 10-fold spatio-temporal CV and forward feature selection via the ffs function from the R package CAST (Meyer et al., 2018). CV folds were created based on the “Cluster” and “Year” features, for space and time, respectively. In combination with spatio-temporal CV, ffs selects those features that in combination lead to the highest classification performance of a RF by excluding all features that lead to overfitting when validated against the left-out Cluster-Year CV-fold. ffs first trains a RF model using all possible feature pairs, keeps the best performing model and iteratively adds each remaining until no additional performance increase is achieved. For this study, spatio-temporal CV was especially important to estimate model transferability to other neighbouring regions such as the Czech Republic and to use the model for generating future projections.

   While ffs is the current best practice in training transferable RF models and to overcome overfitting, it is computationally demanding. Given the size of our final dataset, we therefore used a random sample of 159,744 field-year combinations from Germany and Austria with constant hyperparameters (mtry = 2, ntree = 25).
3. Using the selected features from 3., we then trained our final crop rotation RF model with ten-fold spatio-temporal CV using data from all three countries with mtry = 5 and ntree = 60 after no increase in accuracy was achieved.

Our aim was to arrive at a model that explains the data reasonably well while allowing us to get an understanding of the main drivers determining operational crop rotational decision-making.

To better understand what drives the individual cropping history (according to the rotation model, the most important driver; see Results), we additionally trained an alternative follow-up model, that explicitly excluded all features related to previous crops but used the individual, non-clustered environmental features, again with ten-fold spatio-temporal CV and the same sample from Germany and Austria as for step 2.

We assessed model performance using training and test classification accuracy, confusion matrices, and feature importance values which indicate to what extent the prediction accuracy of the RF would drop if the respective feature would not be considered as a predictor. In reverse, a high feature importance indicates that a feature contributes to a high model accuracy. As ffs selects those features that in combination work best, feature importances may not be interpreted individually. Additionally, features highly correlated with the selected ones might appear as unimportant or not be selected overall, which however helped to identify the true underlying drivers.

### 2.3. Cropping projections

Based on the final model, which predicts the next CType in the rotation based on the selected drivers, we generated a potential outlook of cropping patterns at field level until 2070, the year to which commodity prices are available from GLOBIOM. Many climate change assessment studies project e.g. crop yields into the future. Since we foresee the consideration of real-world crop rotations a generated here as beneficial for such studies, we included a projection period that would align.

For every new year in the projection, $PCType_1$ to $PCType_4$ were derived from CType and $PCType_1$ to $CType_3$ from the previous year. All other features (Cereal_$PCType_4$, deltaP_LEG (based on GLOBIOM price projections), Demand_$PCType_{1,4}$, Drought_$PCType_4$, Fraction_$PCType_{1,3,4}$, func, Organ_$PCType_4$, and Winter_$PCType_4$; see section 3.1 in the Results) were calculated and assigned to each field accordingly, and the new CType was predicted based on the final RF model. To limit unwanted convergence due to systematic bias from uncertain classifications, which would otherwise lead to the extinction of less important crops and the overrepresentation of dominant ones, we introduced stochasticity into the projections. This also accounts for opportunistic cropping choices which are inherent in human behaviour. Specifically, we first assigned the CType with the highest classification probability given the new conditions of each field and year. And second, in very ambiguous cases where the classification probability of the assigned CType fell below the first quantile of classification probabilities across the 17 other CTypes, we assigned a random CType instead of the originally assigned one. In addition, because WW was the most dominant crop overall and more easily confused with other CTypes (see Fig. 4 in the Results), we reassigned a random CType in 22 % of the cases where WW would have been selected. We chose 22 % as a threshold under the assumption that half of the unexplained variance (see Results) reflects opportunistic farmer behaviour, while the other half remains unexplained due to missing data.

Based on this final RF model, we generated a new data set of projected CTypes for each field and each year until 2070, without accounting for potential future changes in field boundaries. We aggregated field-level results to crop share developments per country and across the study region.

## 3. Results

### 3.1. Rotation drivers

Out first RF training attempt, using all potential prediction features and a random split of the data set into 80 %–20 % for training and testing showed a close to perfect (0.99) training accuracy, but only 0.48 for testing (Fig. 2). This large difference between training and testing accuracy indicated severe overfitting of the model. Without targeted CV or feature selection, this RF was heavily dependent on the cluster of environmental features and crop rotations on neighbouring fields, while the importance of agricultural policies and subsidy measures was negligible.

Recognising this, our final model with spatio-temporal CV and forward feature selection (Fig. 3 (a)) omitted overfitting with CType classification accuracy of 0.58 and 0.56 for training and testing, respectively. Further, it reduced the initial set of 75 predictors (Table 3) to 15, grouped into four main categories: most importantly, (i) the field-specific cropping history ($PCType_{1–4}$), followed by (ii) agronomic rules related to this cropping history (Fraction_$PCType_3$, Demand_$PCType_1$, Fraction_$PCType_1$, Demand_$PCType_4$, Drought_$PCType_4$, Organ_$PCType_4$, Fraction_$PCType_4$, Winter_$PCType_4$, Cereal_$PCType_4$), (iii) the functional diversity of the rotation (func), and (iv) the development of legume prices (deltaP_LEG). Interestingly, none of the environmental features, policy measures, or neighbouring information were finally selected. We interpreted these results as a showcase of a “tried-and-tested” behaviour where farmers focus their choices in rotation design on past experience, rather than future opportunity or climate change adaptation potential.

Since it is reasonable to assume that certain crops can and will only be cultivated under conditions that at least enable (if not promote) growth and yield, we hypothesised that the individual cropping history (which was ranked most important) is already a representation of the prevailing environmental conditions. While the alternative model, that explicitly excluded all features related to previous crops but used the individual non-clustered environmental features (Fig. 3 (b)), reduced the train (0.64) and test accuracy (0.34), this follow-up model did indeed reveal the importance of the environmental growing conditions, including the temperature average during summer (TemJJ), silt, func, the state, and the Greening measures of the past CAP. Similarly to the

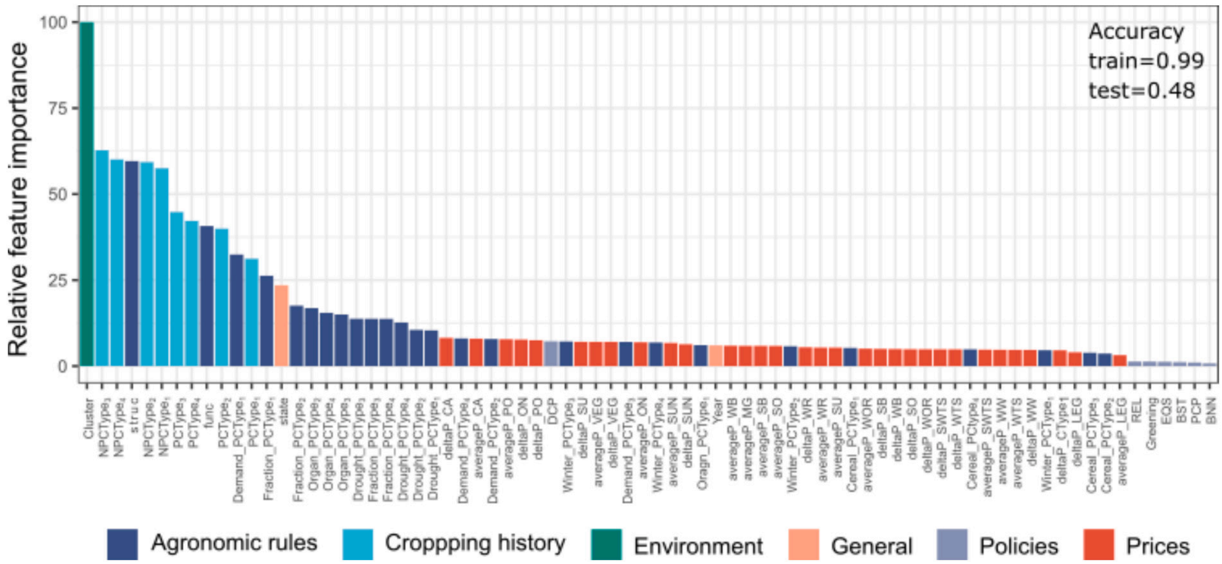


**Fig. 2.** The feature importance of the random forest model without spatio-temporal cross-validation. Features are grouped according to Table 3, also indicating full feature descriptions.

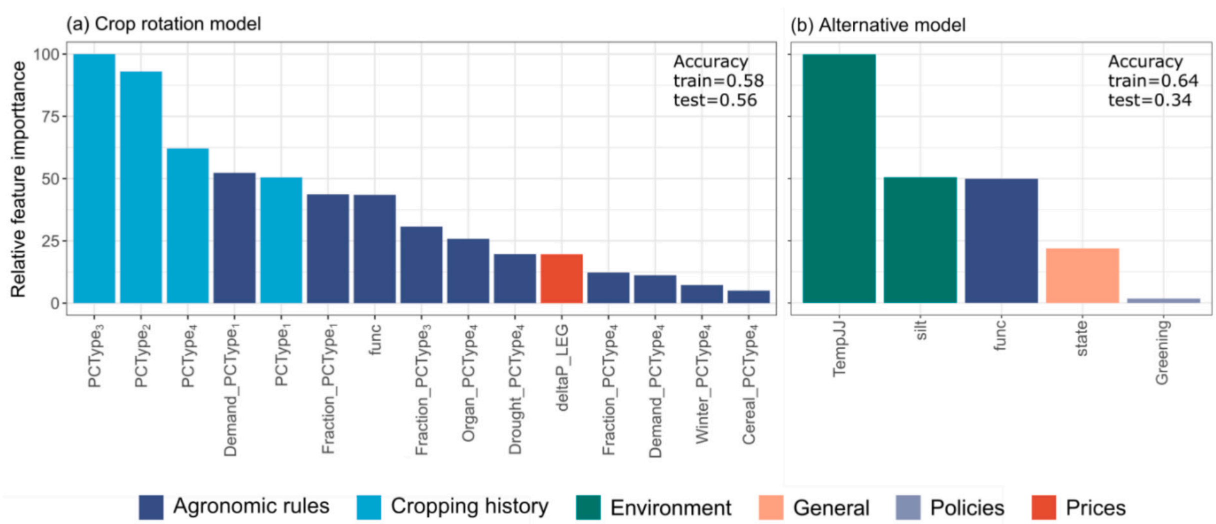


**Fig. 3.** The feature importance of different random forest models. Panel (a) shows the features selected for the random forest model in this study, ranked by importance. Panel (b) shows selected features of the alternative model, excluding all features selected for the first model. The alternative model was used to confirm the hypothesis that the individual cropping history from the crop rotation model is a representation of the prevailing environmental conditions. Features are grouped according to Table 3, also indicating full feature descriptions.

representation of environmental conditions through the cropping history, three out of the eight policy and subsidy measures considered here targeted legume cultivation, either directly (DCP and PCP) or indirectly through qualifying as ecological priority areas (Greening, Table 3). This may have contributed to the development of legume prices and thus to the choice of crop in the rotation, as shown in the first model.

With an overall test accuracy of 0.56, the model predicted the largest share of each CType correctly (indicated by the percentages in the 1:1 diagonal of Fig. 4). We found differing performances for predicting individual CTypes. Winter wheat and silage maize were the most prominent CTypes in the data set and showed the highest accuracies (0.64 and 0.60, respectively). The accuracy for predicting grain maize (0.56) and legumes (0.56) was comparable, however. Further, the model showed a higher degree of confusion of underrepresented CTypes such as carrots (CA), onions (ON), or spring oats (SO), and among CTypes with similar agronomic features e.g. within cereals or leafy crops. A negligible share was confused with carrots, onions, sunflowers, or other leafy vegetables.

### 3.2. *Cropping projections*

To provide a potential outlook on future cropping patterns until 2070 (Fig. 5), we used the final crop rotation model with the 15 selected features, taking into account the stochasticity inherent in farmers' decision-making. Until 2023, rotations were characterised by a high proportion of winter wheat, silage maize, and winter barley. Thereafter, the projections show a more even distribution of crops, with a continued high proportion of winter wheat and silage maize. While the area under winter barley decreases, the area under legumes increases substantially. Legumes have long been promoted, both for their agronomic advantages and for the growing demand for plant-based diets (Drinkwater et al., 1998; Reckling et al., 2016a; Reckling et al., 2016b; Zander et al., 2016; Hazra et al., 2019; Liu et al., 2020; Costa et al., 2021; Notz et al., 2023; Qiao et al., 2024). The development of higher legume cultivation in the recent past, resulting from both price incentives and the gradual change of individual cropping histories, can explain the legume dynamics in the


**Fig. 4.** Confusion matrix for predicting different crop types (CType; MG: grain maize; MS: silage maize; WW: winter wheat; WB: winter barley; WR: winter rye; WTS: winter triticale and spelt; SWTS: spring wheat, triticale, and spelt; SB: spring barley, SO: spring oats; WOR: winter oilseed rape; SU: sugar beet; PO: potato; LEG: legumes; VEG: leafy vegetables; SUN: sunflower; ON: onion; CA: carrot). Numbers within tiles indicate the percentage of actual CTypes predicted as predicted CType. Tinted tiles in y-direction refer to the predicted CType for each actual CType, vice versa for the tiles in x-direction. The 1:1 diagonal represents correct predictions.

projections. We also find higher proportions of winter rye in the future, also referred to as a "resilient crop" (Riedesel et al., 2024), possibly at the expense of winter barley with similar agronomic features (Table 2). Onions and carrots disappear from the projections, which we attribute to their negligible occurrence in our study region.

The projections also show clear differences between the three countries, with differences in growing conditions and past cropping history as the main drivers of crop rotations. Most of the fields were located in Germany (Fig. 1). Therefore, the development of relative crop proportions is in line with the overall distribution in the study region. In Austria, the past distribution of crops differs from the German cropping patterns. While winter wheat was also the most important crop, grain maize came second, followed by potatoes. In the projections, silage maize gains significantly in importance, possibly at the expense of grain maize. We attribute this to a dynamic similar to that of winter wheat and winter barley, with overlapping agronomic features, and partly also to the decreasing proportion of potatoes, while legumes are exceptionally increasing. In the Czech Republic, we find a pronounced importance of winter wheat throughout the projection period, while the remaining crop shares closely follow the distribution of the entire study region.

In addition to the aggregated crop shares, Fig. 6 illustrates an example of future cropping patterns at the field level. Although the newly generated dataset contains CTypes for each field and year up to 2070, we present the example in ten-year intervals for the sake of clarity.

## 4. Discussion and conclusion

By analysing over 16 million data points and 76 covariates using current ML best practices for modelling spatio-temporal data, we identified drivers of operational crop rotation management and provided an outlook on potential future cropping across Central Europe. We found that historical cropping patterns, agronomic rules, and legume commodity prices play a decisive role in shaping crop rotations in the region.

In general, the popularity of ML stems from its ability to achieve high accuracy when analysing complex datasets. Research applications often focus not only on achieving the highest possible prediction accuracies, but also on understanding the dynamics that drive these results. We applied an RF algorithm. Compared to current developments in deep learning (Dupuis et al., 2023), the RF algorithm is considered less complex. However, rather than seeking a more powerful algorithm or tuning the RF for greater accuracy in predicting the type of crop to come, our objective was to identify the key drivers that shape operational crop rotations and based on that to provide a potential outlook on future cropping patterns under unknown space–time conditions. Without targeted training, ML models often replicate relationships well in a specific training dataset but tend to perform poorly when tested on independent data (=overfitting). This often occurs because a model responds disproportionately strongly to feature dynamics that are not independent of the target application—in our case, providing spatio-temporally accurate predictions (Viana et al., 2021; Meyer and Pebesma, 2022). The dataset we used in this study was a prime example. In the initial model,

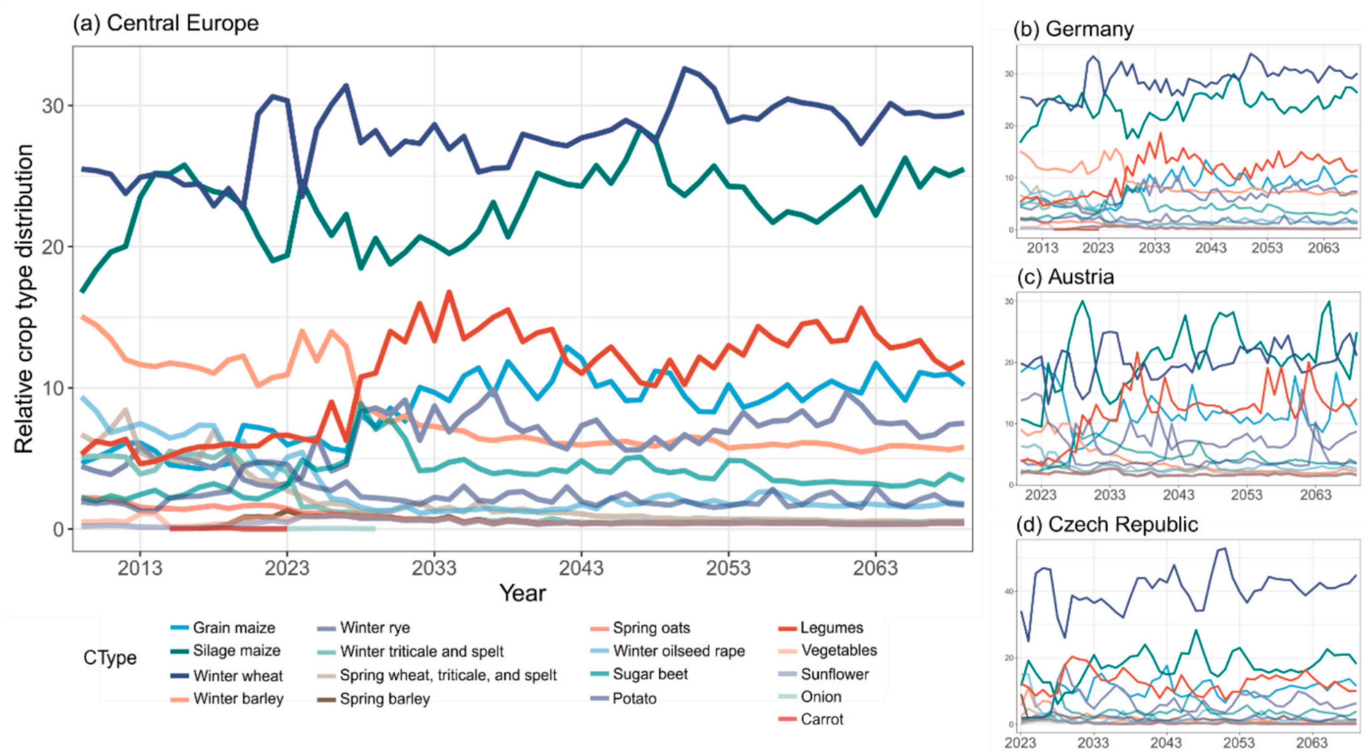


**Fig. 5.** Crop share projections for the study region. Panel (a) shows the projected crop type distribution, with an expected increase in legumes in red. Panels (b) to (d) show country-specific development across the study region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

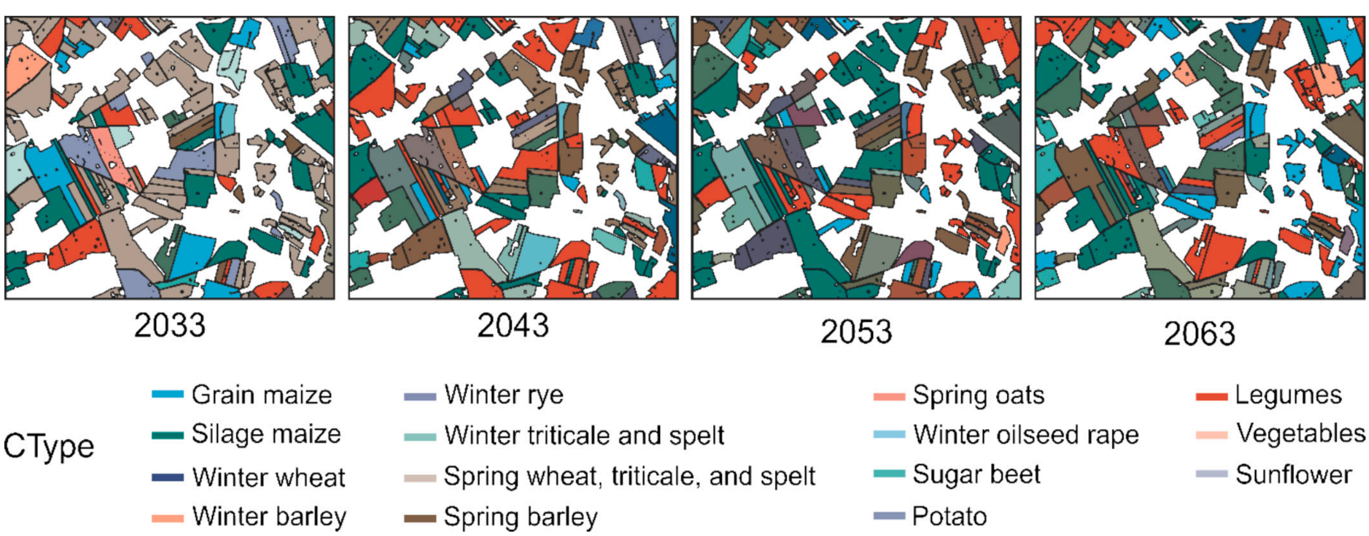


**Fig. 6.** Field specific cropping patterns in ten-year intervals for an example region in Brandenburg, Germany.

the environmental cluster was identified as the most important feature. Since it represents annual weather patterns and site-specific soil conditions, the cluster feature was, of course, highly spatio-temporally dependent. After targeted training, we found our overall accuracy to be comparable to other studies using a similar RF training approach (Meyer et al., 2019; Meyer and Pebesma, 2022), especially given the high resolution of crops into 17 different types. Upcott et al., 2023, for example, reported an accuracy of about 0.7. However, when they excluded long-term grassland from the analysis as we did, the score dropped to 0.4, which is lower than the accuracy we obtained in this study. Another study from France reported coefficients around 0.4–0.6 (Osman et al., 2015), which are comparable to the present ones. Due to data restrictions, we were not able to include whether the fields were part of the same farm or classified as organic or conventional. Previous studies have suggested that organic crop rotations are different from conventional ones (Barbieri et al., 2017; Reumaux et al., 2023) and that rotation planning is not usually done at field level but at farm level (Schönhart et al., 2011; Stein and Steinmann, 2018). Inclusion of these factors may have increased the accuracy in the present study, as may other factors (e.g. farm and field size, livestock density, consumer behaviour, import/export numbers, etc.). However, our aim to generate a model for cropping projections over large spatial and temporal scales meant that only features available at these scales were used.

We found the individual cropping history as the most important driver for shaping crop rotations. As a result of the spatio-temporal dependencies between potential drivers, environmental conditions, market prices and subsidies are likely to have influenced individual cropping histories and were therefore not selected as driving features of our crop rotation model. In line with previous findings (Alfandari et al., 2015; Upcott et al., 2023), our results suggest an average rotation length of four years, as indicated by the importance of the crops grown in the previous four years and the associated agronomic rules. Once a rotation is established, farmers follow this pattern and changes in growing conditions do not significantly affect their crop choices. We interpreted these results as a showcase of a "tried-and-tested" behaviour where farmers focus their choices in rotation design on past experience, rather than future opportunity or climate change adaptation potential. Breaking this habit, for example to increase rotational diversity, appears to remain a challenge (Sietz et al., 2022; Brannan et al., 2023). On the other hand, when the next crop type differed from the one that would be next according to the four-year pattern, we found that agronomic rules played an important role. The availability of planning software (Bachinger and Zander, 2007; Schönhart et al., 2011; Fenz et al., 2023a; Fenz et al., 2023b), easily accessible mobile applications, and the promotion of best practice rules by extension services should therefore not be underestimated. Since individual cropping history plays a decisive role, our findings support farmer engagement and individual crop rotation choices to promote diversified crop rotations (Notz et al., 2023). The four-year rotation length we found is also substantially shorter than the six to eight-year rotations suggested by best practice and differs from the stylised rotations used in crop model simulations for climate change assessment studies. As a result, these studies are likely to underestimate the various benefits and climate change adaptation and mitigation potentials of operational crop rotations and, in particular, higher proportions of legumes (Barbieri et al., 2019). Crop model simulations have been shown to differ significantly when rotation practices are or are not considered (Teixeira et al., 2015; Teixeira et al., 2018; Faye et al., 2023). The effects were particularly pronounced for soil-related variables such as nitrogen fixation amounts, crop residue management, soil organic carbon build-up, and water retention capacity - all important contributors to sustainable and resilient cropping systems – but also for crop yield and greenhouse gas emissions. To arrive at simulations and adaptation studies that better account for these different benefits, we therefore advocate simulation methods that place individual crops in the context of their operational rotation. Our newly generated data set provides one CType for every field and year in the projection period up to 2070. This information can be used directly to inform crop rotation practices for field-level simulations or aggregated into real-world crop masks for gridded crop model applications, for example by assigning each simulation pixel to the crop with the largest area within that pixel. The shapefile data structure makes it possible to generate these crop maps at virtually any resolution. In addition to feeding these derived future patterns into crop models, bio-economic farm or optimization models (Janssen and van Ittersum, 2007; Ermolieva et al., 2015) could directly benefit from constraining the design of their internal crop choices with the drivers we identified. This will ultimately help to design and analyse economic and agronomic scenarios for successfully adapting crop production to a changing climate (Yang et al., 2024).

Additionally, we found that the development of legume prices played a role in determining the type of crop planted next. As legumes gradually became more popular, they played a more important role in the cropping history. They likely became more popular because of their agronomic benefits, including N fixation, and recent increases in legume commodity prices due to higher demand and N (fertilizer price) dynamics. Previous studies have emphasised the trade-off between agronomic and economic benefits of legume cultivation (Preissel et al., 2015; Stagnari et al., 2017; Tzemi et al., 2025) and the potential of price incentives to increase legume cropping (Michalis et al., 2025).

Three out of the eight policy and subsidy measures considered the cultivation of legumes. This may also have contributed to the development of legume prices and thus to the choice of crop type in the rotation as well, highlighting an important lever for promoting more resilient rotations at political level. While the effect of subsidy measures may not be readily apparent and the uptake of new crops may be somewhat delayed (due to the layered identification of rotation drivers and the individual cropping histories as described above), Galioto and Nino (2023) have already shown the importance of financial instruments to encourage crop diversification practices under the CAP reform in Europe. With the introduction of conditional payments under the CAP 2023–2027 (EU, 2022), an estimated 86 % of the EU's arable land is or will be subject to compulsory crop rotations or diversification measures. Providing economic incentives, e.g. in the form of cultivation subsidies for under-represented crops with agronomic advantages for which there is currently no market (such as sorghum, hemp seed, or other minor legumes, could be worthwhile to promote diverse crop rotations across the EU.

For future projections, we developed a simple but effective algorithm that avoids unwanted projection convergence (e.g. limiting the extinction of rare crop types and dominance of a single crop type) by incorporating stochasticity into model time series predictions. However, we recognise that the projections are subject to uncertainty and come with a number of limitations, offering room for future improvements. We had to rely on past knowledge to produce cropping projections. Generational shifts in farmer demographics could gradually change individual preferences and cropping histories. Our crop rotation model may also still confuse crops with similar agronomic features or currently underrepresented crops, such as carrot and onion which, in principle, are economically attractive. The same applies to the projected increase in legume cropping. While a substitution is justifiable from an agronomic or technological perspective, and in addition to the reasons for increased legume cropping as discussed above, projected legumes might still be confused with other spring crops such as silage maize, potatoes, or sugar beet which are projected to decrease. In the case of winter barley, in addition to the justifiable substitution, the decreasing trends might be too pronounced due to confusion with other winter cereals such as winter wheat or winter rye that are on the rise. The underrepresentation of onion and carrot might also be a result of excluding fields with speciality crops, such as herbs or ornamental flowers, which are likely part of horticultural farms where also onion and carrot are grown. Further, we used legume price simulations from the GLOBIOM model, which introduced another layer of uncertainty. GLOBIOM prices showed to behave very differently from past price dynamics, as e.g. unforeseen market shocks are not considered. However, in our model we considered the development of legume prices only as one out of 15 drivers. Using a very restrictive spatio-temporal CV strategy and integrating stochastic decision making, we perceive the present modelling approach as the best-available projection option besides the listed limitations.

Due to the importance of field-specific cropping histories, the application our data-driven analysis and projection of cropping patterns has been limited to regions or countries where well-curated operational cultivation data sets exist, i.e. the IACS data in our case. Yet, recent advancements in remote sensing have shown promising potential for extending our approach to regions where observational crop type data is scarce or not accessible. New products can now estimate crop types at a 10 m resolution over a large geographic extent (Blickensdörfer et al., 2022; Lawes et al., 2022). Ultimately, this will bring new opportunities for crop rotation research as we present here at geographic extents exceeding our present study region.

## Data availability and processing

Open-source IACS data can be found here:

- Austria (years 2015–2023): https://www.data.gv.at/suche/?katFilter%5B0%5D=httppublicationseuropaeuresourceauthoritydata-themeagri&searchterm&typeFilter%5B0%5D=dataset&nr=1&tagFilter%5B0%5D=INVEKOS
- Brandenburg (years 2010–2023): https://geobroker.geobasis-bb.de/gbss.php?MODE=GetProductInformation&PRODUCTID=996f8fd1-c662-4975-b680-3b611fcb5d1f
- Czech Republic (years 2019–2023): https://mze.gov.cz/public/app/lpisext/lpis/verejny2/plpis/
- Lower-Saxony (years 2021–2023): https://sla.niedersachsen.de/landentwicklung/LEA/
- North Rhine-Westphalia (years 2019–2023): https://www.opengeodata.nrw.de/produkte/umwelt_klima/bodennutzung/landwirtschaft/

Digital terrain data is available via https://gdz.bkg.bund.de/index.php/default/digitale-geodaten/digitale-gelandemodelle/digitales-gelandemodell-gitterweite-10-m-dgm10.html and https://www.data.gv.at/katalog/dataset/dgm.

Digital soil maps can be found at https://github.com/zalf-rpm/Buek200_by_CLC and https://bodenkarte.at.

Gridded weather data is available via https://www.dwd.de/DE/leistungen/cdc/cdc_ueberblick-klimadaten.html and https://data.hub.geosphere.at/dataset/spartacus-v2-1d-1km.

FAO producer prices can be found at https://www.fao.org/faostat/en/#data/PP.

Data processing and analysis were performed in the R programming language (R Core Team, 2022, R version 4.2.2) using tidyverse (Wickham et al., 2019), dtplyr (Wickham et al., 2023), sf (Pebesma, 2018), terra (Hijmans et al., 2025), caret (Kuhn, 2008), and CAST (Meyer et al., 2025) packages.

## Author contributions

Conceptualisation: C·N, M.R.; data curation: M.P., L.W., C.J., J.A.G.; formal analysis: M.P., L.W., J.S.; funding acquisition: C·N, M.R.; investigation: M.P., L.W.; methodology: M.P., L.W., M.R.; supervision: C.N., M.R.; validation: M.P.; visualisation: M.P.; writing – original draft: M.P; and writing – review & editing: L.W, J.S., J.A.G., C.J., C.N., M.R.

## CRediT authorship contribution statement

**Marlene Palka:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Claas Nendel:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Lucas Weiß:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Josepha Schiller:** Writing – review & editing, Formal analysis. **Clemens Jänicke:** Writing – review & editing, Data curation. **Juliana Arbeláez Gaviria:** Writing – review & editing, Data curation. **Masahiro Ryo:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The manuscript contains a data and code availability section with a link to the respective GitHub repository.


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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2025.104522.

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