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RESEARCH

Sequential hybridization enhances the reliability of a statistical crop yield model – exemplified by wheat and sugar beet yields in the provinces of Poland

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Abstract

This study uses a data-driven modelling approach to integrate drought indicators and weather data to enhance crop yield simulations. By employing a sequential hybridization method, the research combines drought indices such as SPI, SPEI, or SMI with weather data to refine wheat and sugar beet yield predictions by the statistical model ABSOLUT at the voivodship level in Poland. The modelling approach systematically evaluates possible combinations of 15 input features to identify the most effective configurations for multiple linear regressions. The findings reveal that regression models incorporating both weather data and drought indicators (particularly SPEI and SMI) deliver superior performance compared to those relying solely on weather variables. This improvement is especially pronounced under conditions of variable moisture availability. For example, a model that includes SPEI and weather data more precisely estimates wheat yield, especially during extreme events like the 2018 drought. Additionally, using SMI as the only feature demonstrated that ABSOLUT performed better than when combined with weather data in the case of sugar beet. These results underscore the critical role of incorporating drought indicators to bolster the reliability of crop yield predictions, offering significant insights for agricultural planning in regions susceptible to climatic variability. The research also highlights the potential of hybrid modelling approaches, which combine the strengths of process-based and data-driven models to enhance predictive accuracy. Moreover, the study suggests that these models could be further refined by incorporating additional environmental factors for more robust agro-hydrological simulations.

1 Introduction

In the realm of crop yield modelling, improving modelling accuracy and approaches are among the most critical priorities. There are various agro-hydrological modelling methods, including process-based models, data-driven models, and hybrid models that combine both approaches. These are often called white box, black box, and gray box models, respectively. The accuracy of these models depends largely on the choice and accuracy of their inputs and the efforts of calibration applied (Mensah et al. 2022; Mohammadi et al. 2022; Hu et al. 2024; You et al. 2024; Zhao et al. 2024).

In the process-based approach, empirical equations are employed, requiring the modeler to configure the model with specific inputs before it can generate outputs. On the other hand, data-driven methods require both inputs and observed outputs to identify relationships between them. Gray box models utilize both approaches simultaneously, leveraging each of their strengths (Mohammadi et al. 2022; Hu et al. 2024; You et al. 2024).

Process-based models typically require extensive inputs, such as daily weather data, soil and land use maps, elevation data, basin boundaries, river paths, and management data. These models provide comprehensive information, including river discharge, actual evapotranspiration, nutrient cycles, crop yields, and other water balance components. They also allow for the application of various scenarios, such as land use changes and management strategies.

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Despite their advantages, these models are time-consuming in terms of data acquisition, model setup configuration, and calibration (Bieger et al. 2017; Delavar et al. 2022).

Conversely, data-driven models, such as those based on machine learning and statistical methods, are widely used in hydrology because they can manage large datasets and capture model complexity and non-linear relationships (Mohammadi et al. 2022; Prodhan et al. 2022; Hu et al. 2024). These models can be used with less data for configuration, and advancements in computer science have led to more accurate methods with better computing speeds (Prodhan et al. 2022). However, they have several disadvantages, including a lack of physical insight, poor extrapolation, overfitting, interpretability issues, model transferability, and sensitivity to input variables. Addressing these drawbacks requires approaches that enhance model robustness, interpretability, and applicability.

Reducing errors in data-driven models is possible by applying hybrid approaches, which combine data-driven with process-based models to incorporate physical laws and processes (Li et al. 2023). Additionally, data preprocessing and augmentation can improve model accuracy by using remote-sensed data, satellite-based products, and other supplementary data sources to fill gaps and enhance datasets (Eini et al. 2023a). Cross-validation techniques, regularization methods, model pruning, and simplification are potential solutions to mitigate overfitting. To increase the reliability of data-driven models, researchers can employ explainable Artificial Intelligence (AI) and automated feature selection to improve transparency and reduce dimensionality. Comprehensive validation across independent temporal and spatial datasets is also essential for ensuring robust model performance. Furthermore, hybrid modeling offers a significant advantage by utilizing data augmentation to add physical insight to the statistical predictions. Together, these approaches ensure that complex predictive models remain both accurate and scientifically interpretable (Fleming et al. 2021; Dong et al. 2023; Li et al. 2023).

Three main architectures of hybrid modeling can be distinguished: sequential hybridization, parallel hybridization, and integrated hybridization (Hajirahimi and Khashei 2019, 2022).

- **Sequential hybridization**, the method employed in this study, involves models coupled in a series where the output of a process-based model serves as the input for a data-driven model.
- **Parallel hybridization** occurs when different models operate simultaneously on the same or separate datasets, and their individual results are subsequently combined, often through ensemble techniques, to produce a final prediction.
- **Integrated hybridization** represents a deep coupling where components of a process-based model (such as physical equations) are directly embedded within the mathematical framework of a data-driven model (such as a neural network's loss function) to ensure physical consistency.

In the sequential hybridization method, calibrated process-based models can be used as a source of input data through two primary pathways: direct output augmentation, where simulated variables are used as primary predictors, and the indirect approach, where the process-based model generates synthetic historical scenarios or 'pseudo-observations' to fill gaps in sparse empirical datasets. For example, basin-wide distributed process-based models, such as the Soil and Water Assessment Tool (SWAT), provide time-varying fields—such as soil moisture (SMI), actual evapotranspiration, and Leaf Area Index (LAI)—for the entire area of the modeled basin (Bieger et al. 2017; Eini et al. 2020; Zhao et al. 2024). These datasets can be added to data-driven models as an auxiliary input to augment datasets for various purposes, such as river discharge predictions, crop yield simulations, drought predictions, and groundwater recharge estimations (Fleming et al. 2021). Integrating process-based model outputs with data-driven models offers a robust and effective approach to enhance predictive accuracy. This approach leverages the detailed, process-based insights from physical models and the advanced pattern recognition capabilities of data-driven models, resulting in a comprehensive tool for agricultural planning and water resources management (Mohammadi et al. 2022; Prodhan et al. 2022; Dong et al. 2023).

Various hydrological studies have recently employed sequential hybridization of process-based and data-driven models. For instance, researchers have combined the SWAT model with machine learning methods to improve the prediction of streamflow and water quality (Senent-Aparicio et al. 2019; Noori et al. 2020). Also, SWAT outputs such as soil moisture and evapotranspiration were used as inputs to a data-driven model, significantly enhancing the accuracy of streamflow and sediment predictions in complex watersheds (Jimeno-Sáez et al. 2022; Islam et al. 2023). Another example involves coupling the Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS) with Support Vector Machines (SVM) to predict peak river flows during extreme weather events (Young et al. 2017). By leveraging the physical accuracy of HEC-HMS and the pattern recognition capabilities of SVM, the hybrid model provided more reliable forecasts of flood risks (Young et al. 2017).

Moreover, hybrid models have been employed in groundwater studies (Milan et al. 2018, 2021). For instance, the MODFLOW model, which simulates groundwater flow, has been combined with neural networks to predict groundwater levels under varying climatic and pumping conditions (Moghaddam et al. 2019). This approach allows for more adaptive water resource management by improving the responsiveness of groundwater models to changing environmental conditions.

In agricultural water management, coupling or comparisons of process-based models with data-driven approaches such as Gradient Boosting Machines (GBM) or ANNs have been utilized to predict crop yields more accurately (Jin et al. 2018; Lei et al. 2023; Hu et al. 2024). However, crop yields are influenced by various factors, including climate, management practices, soil properties, and extreme events such as heat waves or droughts (Zhu et al. 2022; Hu et al. 2024).

As mentioned, data augmentation is one approach that can increase the accuracy of data-driven methods. Data augmentation can be a direct or indirect output of a process-based model (Young et al. 2017):

- **Direct Output Augmentation**: This involves the direct use of variables simulated by a process-based model (e.g., soil moisture, actual evapotranspiration) as supplementary predictors within the statistical model. This study primarily focuses on this approach by integrating SWAT-derived drought indicators.
- **Indirect Data Augmentation**: This approach utilizes the process-based model to generate large-scale synthetic datasets or 'pseudo-observations' based on historical climate scenarios. These synthetic data are used to 'pre-calibrate' or train the data-driven model, effectively filling gaps in empirical records and improving the model's robustness in regions where long-term historical yield data are limited.

By combining these two approaches, researchers can leverage the physical consistency of process-based models to enhance the predictive power of statistical tools, particularly in complex agricultural systems.

For instance, calculating drought indicators, such as the Soil Moisture Index (SMI) and Standardized Precipitation Evapotranspiration Index (SPEI), and using them as inputs to a data-driven model is an example of indirect data extracted from a process-based model.

Drought risk is an important constraint on agricultural production in Poland. Recent severe drought episodes, including the dry sequence of 2018–2020, demonstrated that precipitation deficits combined with high evaporative demand can lead to low soil moisture and substantial agricultural stress. Previous studies have shown that drought conditions in Poland are spatially differentiated, with central and southwestern regions being particularly exposed during parts of the growing season (Eini et al. 2023c). Agricultural drought monitoring in Poland also relies on indicators related to precipitation anomalies, climatic water balance, soil moisture, and potential yield reduction, highlighting the direct relevance of moisture-stress indicators for crop-yield assessment (Jędrejek et al. 2022). Therefore, incorporating drought indicators such as SPEI and SMI into statistical yield models is expected to improve the representation of water-limitation effects that may not be fully captured by meteorological variables alone.

This study aims to enhance the predictive reliability of the ABSOLUT v1.2 statistical crop yield model (Conradt 2022) by implementing a sequential hybridization framework across Poland's provinces. The core innovation lies in systematically augmenting traditional weather-driven simulations with process-based drought indicators (SMI and SPEI) derived from the Soil and Water Assessment Tool (SWAT). By leveraging these auxiliary datasets as supplementary predictors, we hypothesize that incorporating physically consistent moisture-stress variables will significantly improve the accuracy of wheat and sugar beet yield predictions compared to reference models that rely solely on meteorological parameters. Rather than evaluating drought indicators solely as performance enhancers under extreme conditions, this study assesses their role in improving the robustness and physical consistency of statistical crop yield models across both typical and stress-prone years.

2 Materials and methods

This section refers to the study area, employed datasets, the crop yield model, utilized drought indicators, and crop yield simulation approaches.

2.1 Study area

Poland, located in central Europe, is selected as the case study for this research. The country features diverse landscapes, ranging from the Baltic Sea in the north to the Carpathian and Sudeten Mountains in the south (Eini et al. 2026). The central part of Poland is dominated by the North European Plain, which supports extensive agriculture with its rich soils. Poland's agricultural production conditions are spatially heterogeneous and should not be interpreted as uniformly favorable across all lowland areas. The quality of agricultural production space depends not only on climate but also on soil quality, agricultural suitability, agroclimate, relief, and soil-water conditions. According to the agricultural production space valorization framework used in Poland, the most favorable natural conditions for agricultural production occur in regions such as Opolskie, Dolnośląskie, Lubelskie, and Kujawsko-Pomorskie, whereas less favorable habitat conditions occur, for example, in Podlaskie and parts of Mazowieckie. This spatial heterogeneity is relevant for yield modelling, because wheat and sugar beet responses to drought indicators may be affected by local soil-water retention, soil fertility, and crop specialization patterns. Therefore, in the present study, the term "favorable agricultural conditions" is used in a regional sense rather than as a uniform characterization of all Polish lowlands. In this study, crop yield datasets were used at the province level. Poland is divided into 16 administrative provinces, known as "voivodeships" (Fig. 1).

Poland experiences a temperate climate, influenced by both maritime and continental factors. The average annual temperature ranges from 6 to 8 °C across the study area. The warmest regions are the Silesian Lowland and Sandomierska Upland, while the coldest area is located in Suwałki, on the northeastern edge of the country. Winters are typically cold and snowy, especially in the mountainous regions, while summers are warm and moderately humid. Precipitation is distributed throughout the year, averaging about 600 mm/yr, with higher amounts in the summer months and regional concentrations in the vicinity of the Baltic Sea, especially in the southern, mountainous areas, where annual averages can exceed 1000 mm/yr (CCKP 2024). This climatic diversity supports a variety of crops, including wheat, barley, rye, maize, rape seed, potatoes, sugar beet, and fruits such as apples and berries. Additional information on agro-hydro-meteorological variables for Poland can be found in Marcinkowski et al. (2023). The favorable growing conditions have made Poland one of the leading agricultural producers in Europe, contributing significantly to the nation's economy.

In 2022, the gross value added (GVA) of Poland's agriculture, forestry, and fishing sectors was reported at 87,118 million PLN (~21,780 million USD) (CEIC 2024). This sector contributed approximately 2.9% to Poland's gross domestic product (GDP) in the same year (Statista 2024). According to Eurostat, Poland is the second-largest producer of wheat and the third-largest producer of sugar beet in the EU (Eurostat 2024).

2.2 Statistical crop yield simulator

The ABSOLUT model (Conradt 2022) uses monthly weather datasets to simulate crop yields and, consequently, employs an out-of-sample approach in the feature and regression selection steps. The model, written in the R programming language (https://www.r-project.org/, last access: 2 February 2026), with sample datasets is freely available on Zenodo (https://doi.org/10.5281/zenodo.5789350, last access: 2 February 2026). It has been tested and used in a few studies, such as those by Conradt (2022) and Nishizawa et al. (2023).

The ABSOLUT model (Conradt 2022) is an automated statistical simulator designed to identify the optimal relationship between agro-climatic predictors and crop yields. The core of the simulator is a Multiple Linear Regression (MLR) engine that operates through an iterative feature selection process. Specifically, the model evaluates a vast search space of potential predictor combinations, including monthly averages of temperature, precipitation, and, in this study, hybridized drought indicators. To ensure the

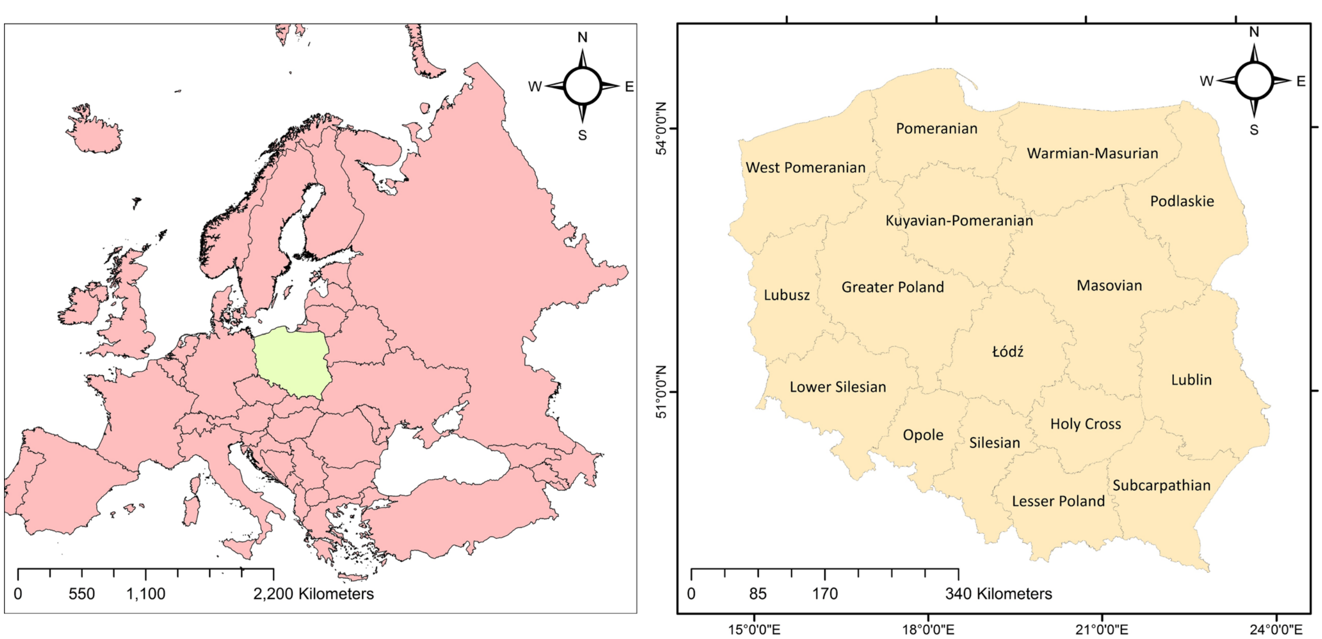


Fig. 1 The location of Poland in Europe and the Polish voivodeships

reliability of the resulting regression, ABSOLUT employs an out-of-sample validation strategy:

1. **Exhaustive Search**: It tests various combinations of monthly climate variables across the growing season.
2. **Performance Metrics**: It ranks these combinations based on their predictive power (using R^2 and RMSE) while penalizing for overfitting through criteria like the Akaike Information Criterion (AIC).
3. **Robustness Check**: The model prioritizes configurations that demonstrate stability across different sub-periods of the historical record, ensuring that the selected predictors represent physical drivers of yield rather than statistical noise.

This process allows the simulator to autonomously determine which specific months and indicators (e.g., SMI in June vs. SPEI in May) are most critical for the target crop in a specific region, effectively acting as an automated 'feature engineer' for crop-weather relationships.

To address potential multicollinearity arising from high correlations between certain drought indicators at overlapping timescales (e.g., SPEI-9 and SPEI-12, as shown in Fig. 6), the ABSOLUT simulator incorporates internal safeguards. The feature selection algorithm evaluates predictors not only for their individual correlation with yield but also for their collective contribution to the regression model. By employing the Akaike Information Criterion (AIC), the model penalizes the inclusion of redundant variables that increase model complexity without a significant improvement in predictive power. Furthermore, the out-of-sample validation strategy ensures that the selected configurations remain stable across different sub-periods. If two predictors are highly collinear, the algorithm typically selects the one with the stronger physical signal, while excluding the other to maintain model parsimony and avoid unstable coefficient estimates. Figure 2 presents the flowchart of ABSOLUT.

2.3 Weather and crop yield datasets

We selected a 2-km regional gridded dataset (G2DC-PL+, Piniewski et al. (2021) to extract the climatic data. This dataset has been used in several studies and has shown high accuracy in agro-hydrological modelling and assessments (Eini et al. 2023b; Marcinkowski et al. 2024). It contains daily precipitation, minimum temperature, maximum temperature, wind speed, and relative humidity for the entire Poland and the Vistula and Odra (Oder) transboundary river basins over 69 years, 1951–2019. The dataset is publicly accessible from the 4TU Centre for Research Data in NetCDF and TIF formats at https://doi.org/10.4121/uuid:a3bed3b8-e22a-4b68-8d75-7b87109c9feb (last access: 18 May 2026).

Crop yield datasets and the cultivation areas for the period 1999–2019 from the Central Statistical Office of Poland were used in this study (the dataset had been obtained from https://stat.gov.pl/en/national-census/ (last access: 5 November 2024)). The average yield of wheat is approximately 40 dt/ha (varying between 16 and 65 dt/ha), and the average sugar beet yield is 508 dt/ha (ranging between 256 and 938 dt/ha). Figure 3 shows wheat and sugar beet yields in Poland. Figure 4 provides the spatial distribution of wheat and sugar beet yields (dt/ha) and cultivation area (ha).

2.4 Model-based spatial dataset

The SWAT model is a widely used agro-hydrological model, tested in numerous catchments with diverse climatic conditions for different aims, such as surface-groundwater interactions, the effect of climate change on hydrology, ecosystem services, land use change assessments, and water quality modelling (Gassman et al. 2007; Mahdavi and Ghorbanizadeh Kharazi 2023; Salmani et al. 2023; Plunge et al. 2024; Zhao et al. 2024).

Spatial datasets, including selected daily water balance components such as soil moisture and potential evapotranspiration, were extracted from the SWAT model setup covering the entire territory of Poland (Marcinkowski et al. 2023). This comprehensively calibrated model provides high-resolution water balance and streamflow datasets for 1951–2019for 4,381 sub-basins in netCDF format and is described in Marcinkowski et al. (2023). The model underwent comprehensive calibration and validation using a two-stage, multi-site approach across 88 river discharge stations in Poland. The simulations demonstrate acceptable performance, achieving a median Kling–Gupta efficiency (KGE) of 0.73 during calibration and 0.70 during validation. This model and its outputs were used in several studies, such as Marcinkowski et al. (2024), Marcinkowski and Piniewski (2024), Venegas-Cordero et al. (2024), Venegas-Cordero et al. (2023). Spatially weighted averages for each province in Poland were calculated and then used to calculate drought indicators.

2.5 Drought indicators

Two drought indicators, the Soil Moisture Index (SMI) (Svoboda and Fuchs 2016) and Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010) were calculated from the SWAT outputs. In addition, the Standardized Precipitation Index (SPI) was computed directly from precipitation datasets. These

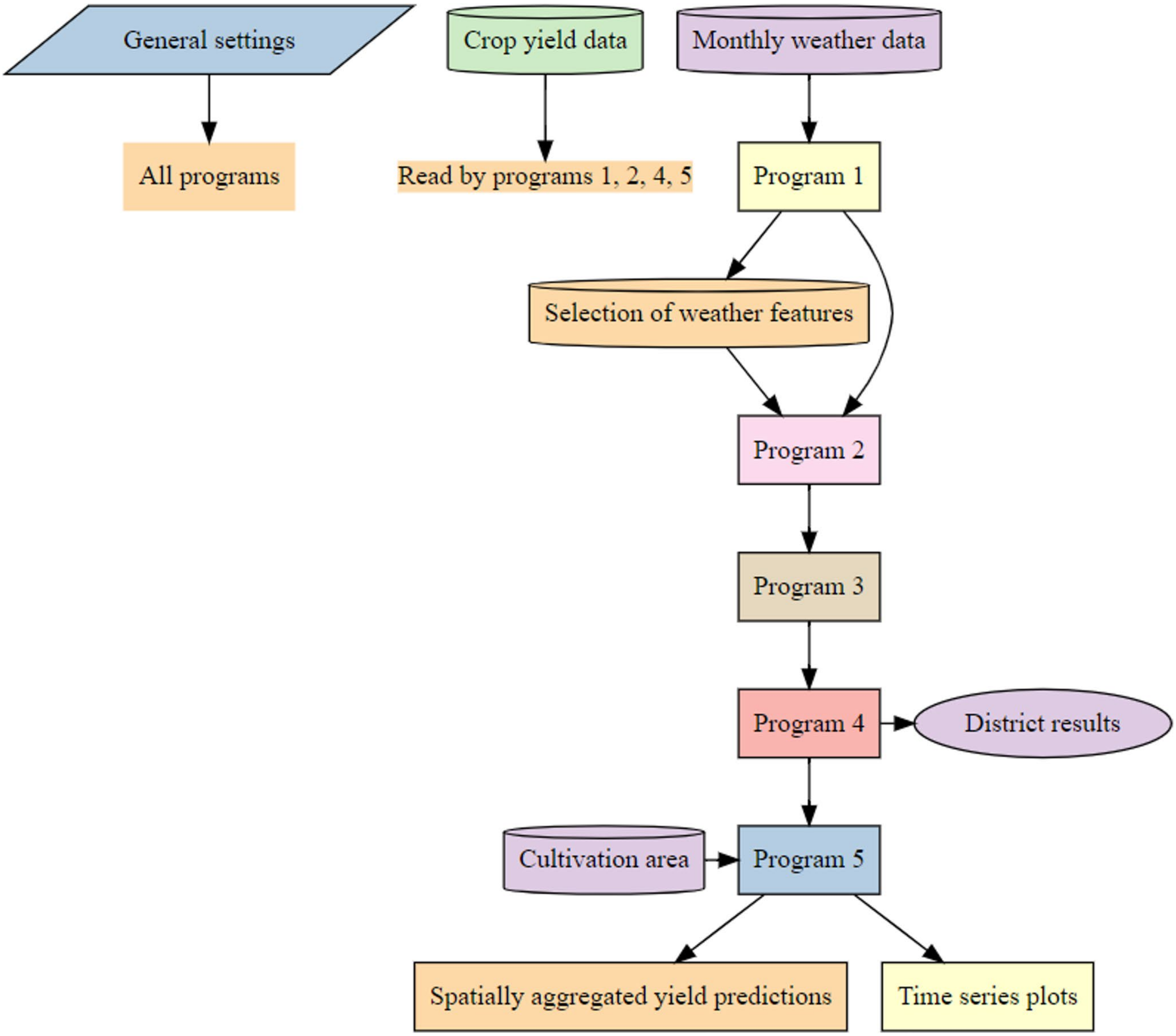


Fig. 2 Flowchart of ABSOLUT

indices are crucial for assessing drought conditions and understanding their impact on agricultural productivity. The SMI provides insights into soil moisture levels, which are vital for crop growth and water availability, while the SPEI accounts for precipitation and potential evapotranspiration to evaluate the overall moisture balance. Conversely, the SPI focuses exclusively on precipitation anomalies, helping to detect dry and wet phases. By incorporating these indicators into our analysis, we aim to enhance the accuracy of crop yield predictions and better understand the relationship between climatic variables and agricultural yields (AghaKouchak 2014; Laaha et al. 2017; Modanesi et al. 2020).

SPI and SMI were calculated based on the Gamma distribution (suggested by McKee et al. (1993), and for SPEI, the log-logistic distribution was employed (suggested by Vicente-Serrano et al. (2010). The maximum length of the data (1951–2020) was used to calculate these drought indicators. Then, the drought indicators from 1990 to 2020 were used as input for the ABSOLUT model. The R programming language and the CDT package in R (Climate Data Tools: available at https://github.com/rijaf-iri/CDT) were used to calculate SPI, SPEI, and SMI.

These drought indicators were calculated for four selected accumulation periods: 3, 6, 9, and 12 months, representing short-term and medium-term drought impacts. While the three-month (SPI-3, SPEI-3) and six-month (SPI-6, SPEI-6) indicators capture sub-seasonal to seasonal impacts, the 9 months (SPI-9, SPEI-9) and twelve-month (SPI-12, SPEI-12) indicators reflect longer scales capturing prolonged

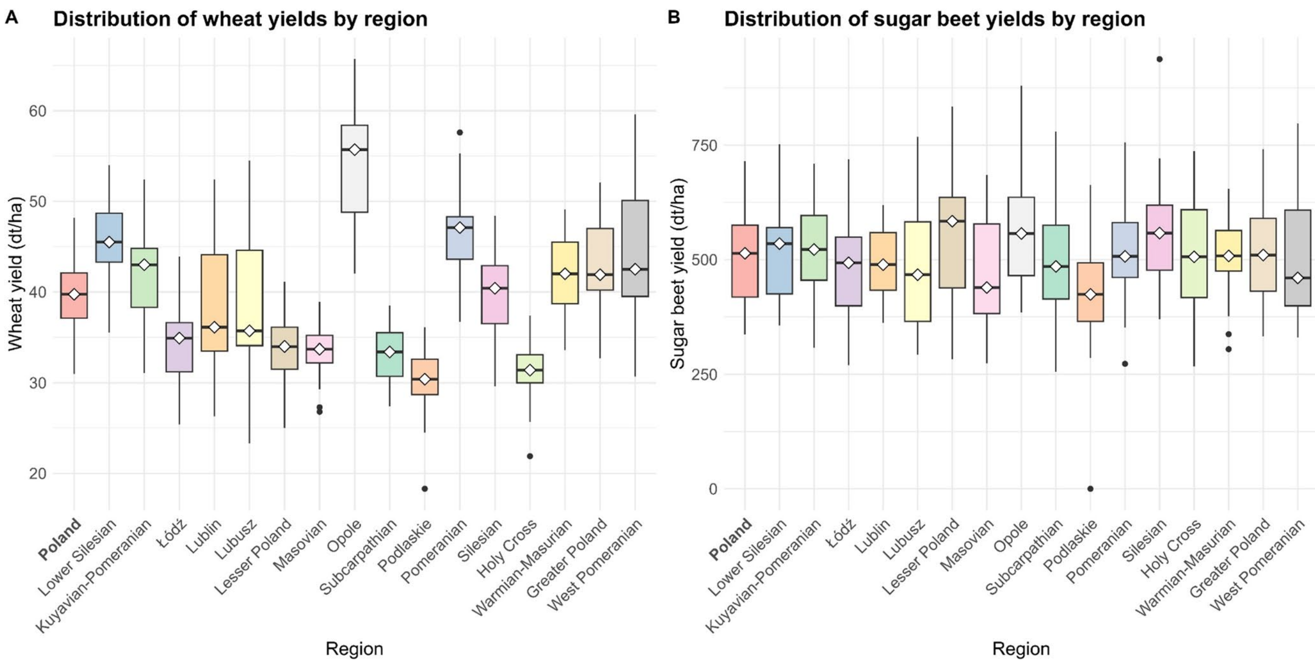


Fig. 3 Historical wheat and sugar beet observations in Poland for the period 1999–2019 – boxplot by voivodeships and Poland. (source of data: Central Statistical Office): the central horizontal line represents the median; the bottom and top edges of the box represent the first (25th) and third (75th) quartiles, respectively (the interquartile range); the whiskers extend to the minimum and maximum values excluding outliers; and any individual points plotted beyond the whiskers represent outliers

moisture deficits. Figure 5 shows the monthly and annual average of SPEI in Poland.

2.6 Experiment design

To evaluate the added value of drought indicators in crop yield forecasting, we designed an experiment involving 15 distinct predictor combinations (labeled 'a' through 'o' in Table 1).

These combinations were structured to systematically test the influence of:

1. Individual drought indicators (e.g., SMI only, SPEI only).
2. Aggregated indicators (e.g., combinations of SPI and SMI).
3. Hybridized sets (weather datasets augmented with one or more drought indices).

Each configuration was evaluated against a 'Reference' set containing only standard meteorological data. By comparing the performance metrics (R^2, RMSE) across these 15 combinations, we could isolate the specific contribution of each hydrological variable to the overall predictive accuracy of the system. Model improvement is assessed primarily in terms of long-term predictive stability (R^2 and RMSE over multiple years), rather than isolated single-year spatial differences, which may reflect transient or non-climatic effects.

The voivodeship level was used because the official crop-yield and cultivation-area statistics employed in this study are reported at this administrative scale. Using the same spatial unit for observed yields, cultivation-area weighting, meteorological predictors, and SWAT-derived drought indicators ensured consistency between input and target variables. Although agrometeorological regionalization could better represent spatially homogeneous crop-climate-soil conditions, it would require yield observations and crop-area statistics to be available for those regions. Therefore, the administrative division was selected as a practical compromise between data availability, statistical consistency, and national-scale applicability.

It should be noted that ABSOLUT selects only a few from the up to 20 single features offered in the end. Figure 6 shows the matrix correlation between all inputs and reveals the additional value drought indicators add to the model. According to Fig. 6, the drought indicators are highly correlated within their groups, and the same holds for the group of weather variables, including strong anti-correlations with humidity. There are, however, hardly any connections between drought indicators and weather datasets. As shown in Fig. 7, three data sources were employed as inputs to the ABSOLUT model. Simulated crop yields and the most frequent features were extracted from the model and used in this study.

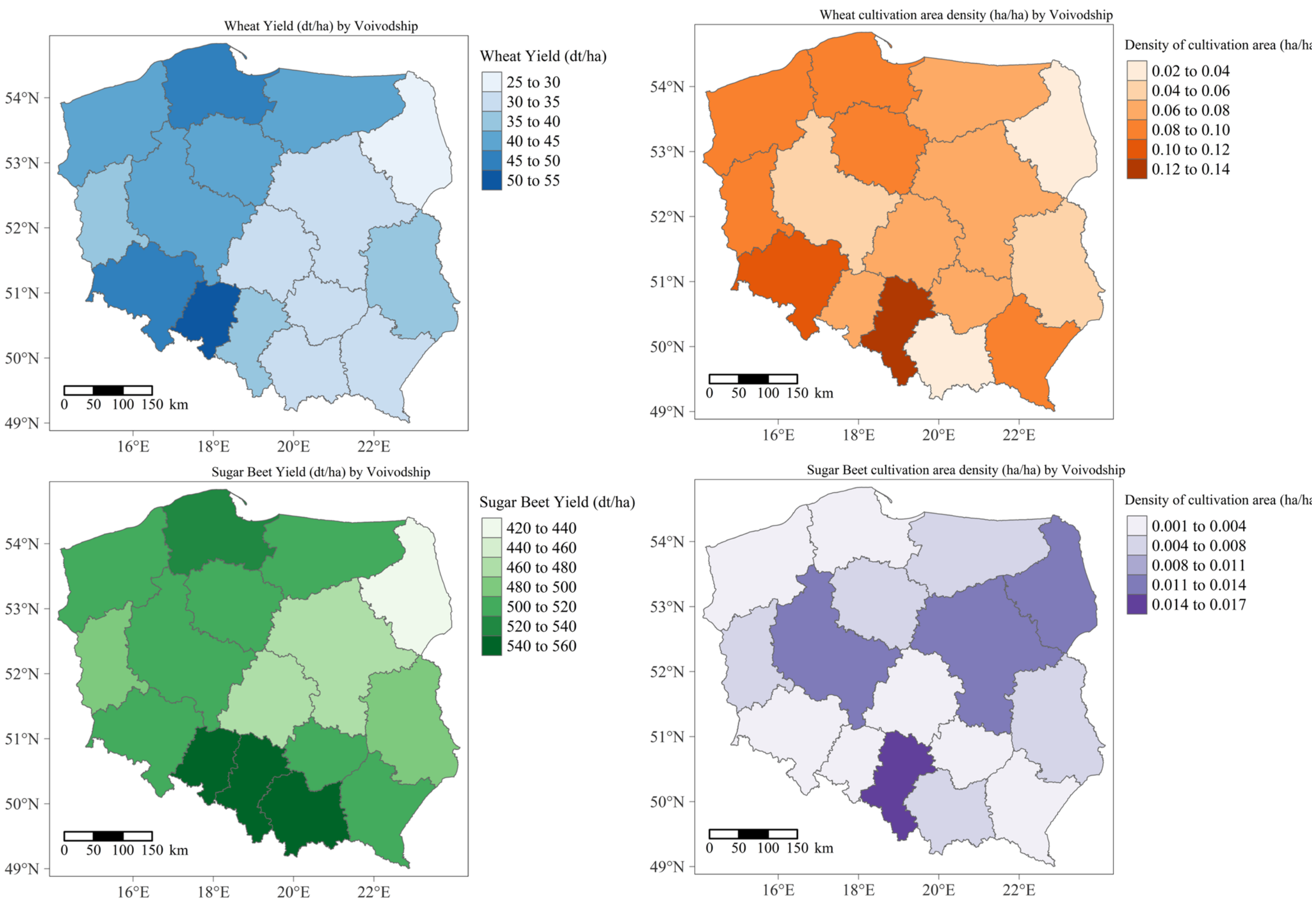


Fig. 4 Spatial distribution of average wheat and sugar beet yields (dt/ha) and density of cultivation area (ha/ha) in Poland by voivodeships. (source of data: Central Statistical Office)

3 Results

In this section, results based on the different inputs are provided. Then, the best configurations are investigated, and the most influential parameters are determined.

3.1 Model's accuracy over Poland

The period from 1999 to 2018 was used for crop yield simulations based on the weather-related input features presented above and the observed yield time series. This long-term out-of-sample validation provides the primary basis for assessing overall model reliability, while the subsequent spatial analyses focus on illustrating regional behavior in a selected prediction year. The ABSOLUT model aggregates the best regressions from each spatial subunit (here, voivodeships) and then provides average crop yields for the entire country using cultivation areas as weighting factors. Table 2 shows the overall accuracy of configurations for wheat and sugar beet yields in Poland by R-squared and RMSE (Root Mean Squared Error) based on a leave-one-out validation (Li et al. 2019; Dinh and Aires 2022). Figure 8 presents the annual simulated and observed crop yields, spatially averaged over Poland, for all configurations. Figure 9 shows the distributions of simulated wheat yields across all configurations and years, compared with observed data in Poland. It can be noted that all configurations' average yields are higher than the observation record.

Based on Table 2, two configurations were selected for further investigation in wheat simulations: the reference configuration (only using weather datasets) and the configuration that also used SPEI, which achieved the highest R-squared and RMSE. Although the configuration based on SPI and weather datasets also performed very close to this optimum in wheat yield simulations, it was excluded because of the high correlation between SPI and SPEI, as shown in Fig. 6.

For sugar beet yields, the configuration that used only SMI performed better than the reference and any of the other configurations (Table 2). Combining SMI with SPI and SPEI also yielded improved performance compared to the reference configuration, underscoring the importance of SMI. These results indicate that drought indicators can serve as influential variables in statistical crop yield models.

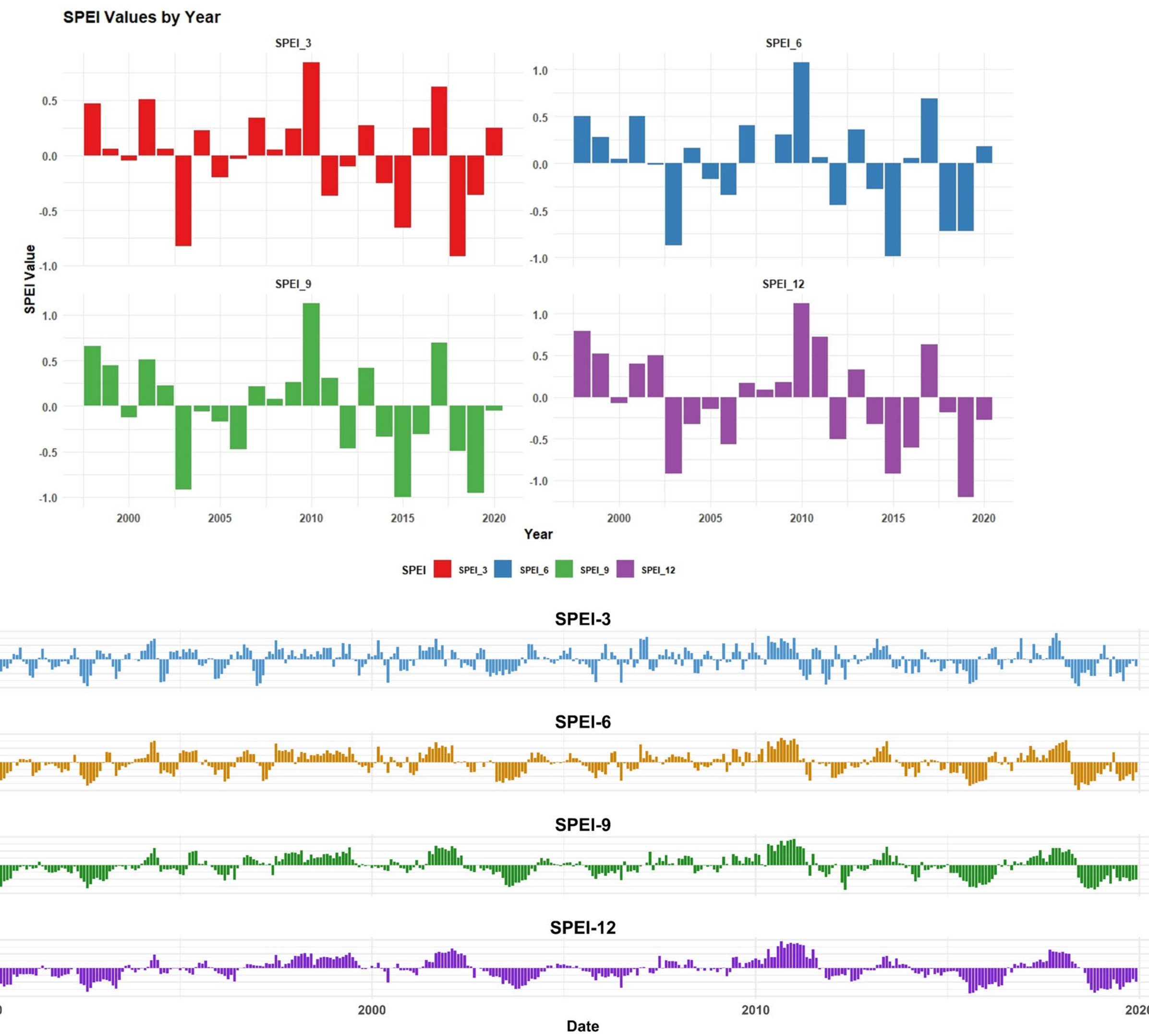


Fig. 5 Annual and monthly SPEI (Standardized Precipitation Evapotranspiration Index) values over time for different accumulation periods in Poland

Table 1 Designed configurations and selected inputs

Configuration	Inputs			
a	SPEI			
b	SPEI	SPI		
c	SPEI		SMI	
d	SPEI			Weather data
e	SPEI	SPI	SMI	
f	SPEI	SPI		Weather data
g	SPEI		SMI	Weather data
h	SPEI	SPI	SMI	Weather data
i		SPI		
j		SPI	SMI	
k		SPI		Weather data
l		SPI	SMI	Weather data
m			SMI	
n			SMI	Weather data
Reference				Weather data

In a similar approach using weather variables only, i.e., without drought indices, Conradt (2022) applied the ABSOLUT model to simulate the yields of silage maize and winter wheat in Germany. The study utilized 20 years of data from approximately 300 districts. The model's accuracy in simulating winter wheat yields in Germany, with an R-squared of 0.417 and an RMSE of 4.58 (dt/ha), was lower compared to the results of the present study. However, in recent tests over Germany (done by Conradt (2024), personal discussion), SPEI-12 increased the accuracy of winter wheat simulations to an R-squared of 0.48 and an RMSE of less than 4 dt/ha.

Given that Germany and Poland are both located in Central Europe and share similar climatic conditions, our results indicate that ABSOLUT performed better in Poland. However, differences between Germany and Poland include the

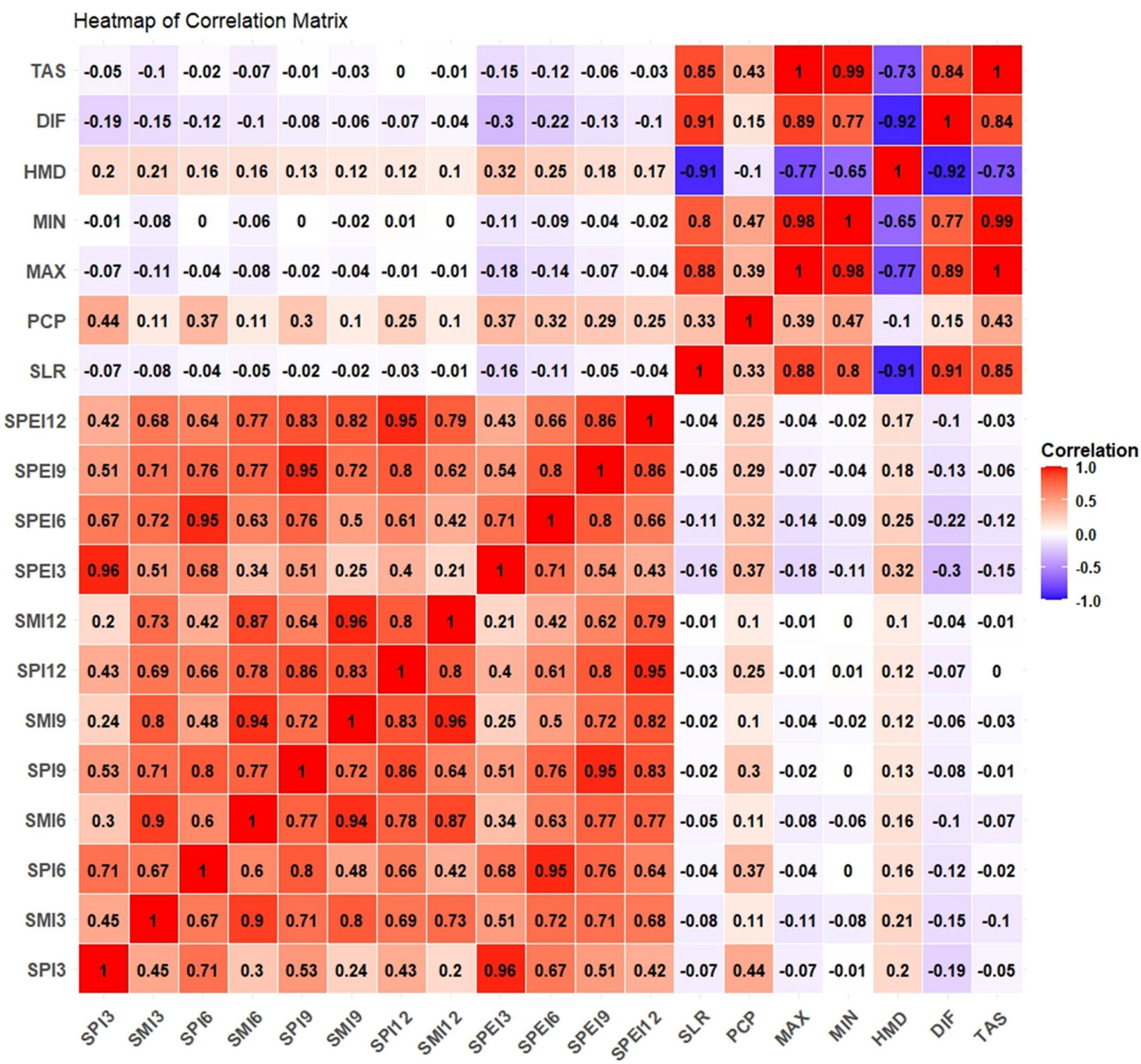


Fig. 6 Heatmap of matrix correlation between all inputs

smaller size of German districts (more observation noise) and the greater diversity of German landscapes, which leads to a greater number of microclimates – a harder challenge for the model to find representative feature combinations.

3.2 Crop yield simulations based on weather data

To complement the long-term validation, we analyze the spatial performance of selected configurations for the year 2019 as a diagnostic case study, rather than as a standalone measure of model skill. The year 2019 was chosen for detailed spatial validation as it represents the final year of the dataset, providing a measure of the model's predictive capability on the most recent independent data. Climatologically, 2019 in Poland was characterized by relatively high yields but featured localized soil moisture deficits during the late spring, making it a suitable test case for assessing regional model behavior and robustness under predominantly near-normal moisture conditions."Table 3 provides the reference configuration's accuracy in 2019 (predictions based on weather data). The RMSE values vary substantially over provinces, ranging from 2.35 dt/ha for the Subcarpathian voivodship to 7.55 dt/ha for the Lubusz voivodship (wheat) and from 52 dt/ha for the Pomeranian voivodship to 154.8 dt/ha for the Podlaskie voivodship (sugar beet). Yields are overestimated in nearly

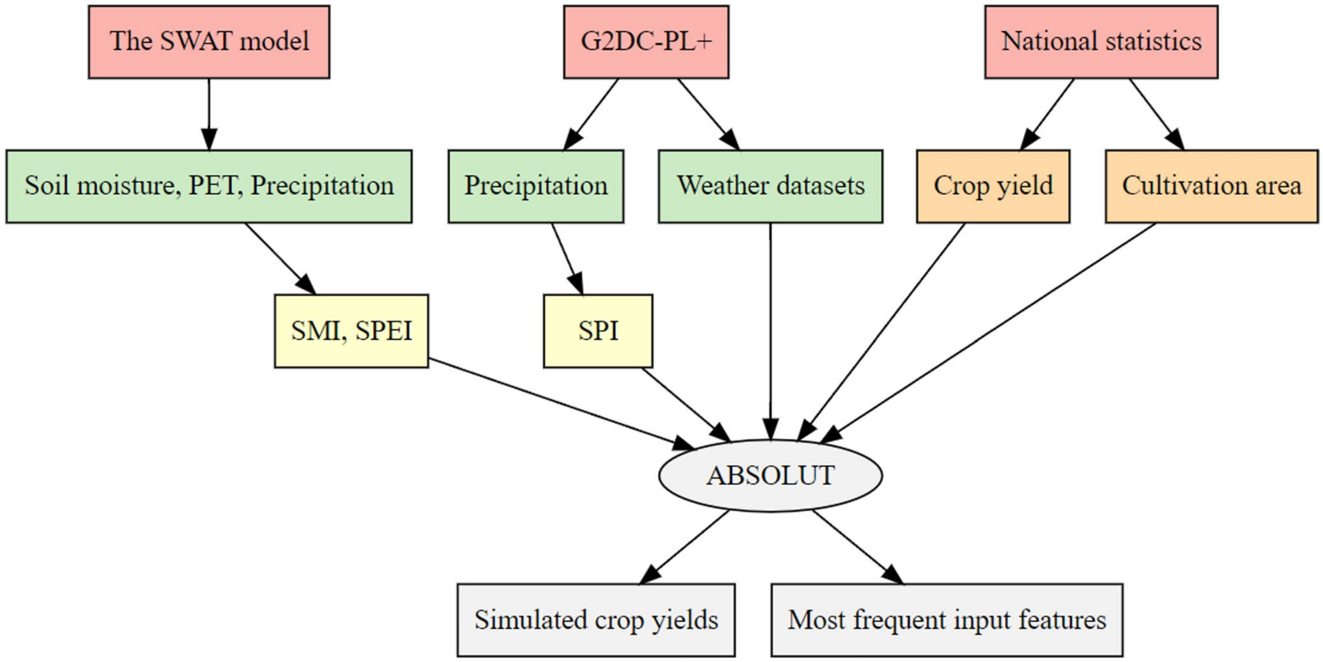


Fig. 7 Flowchart of the current study

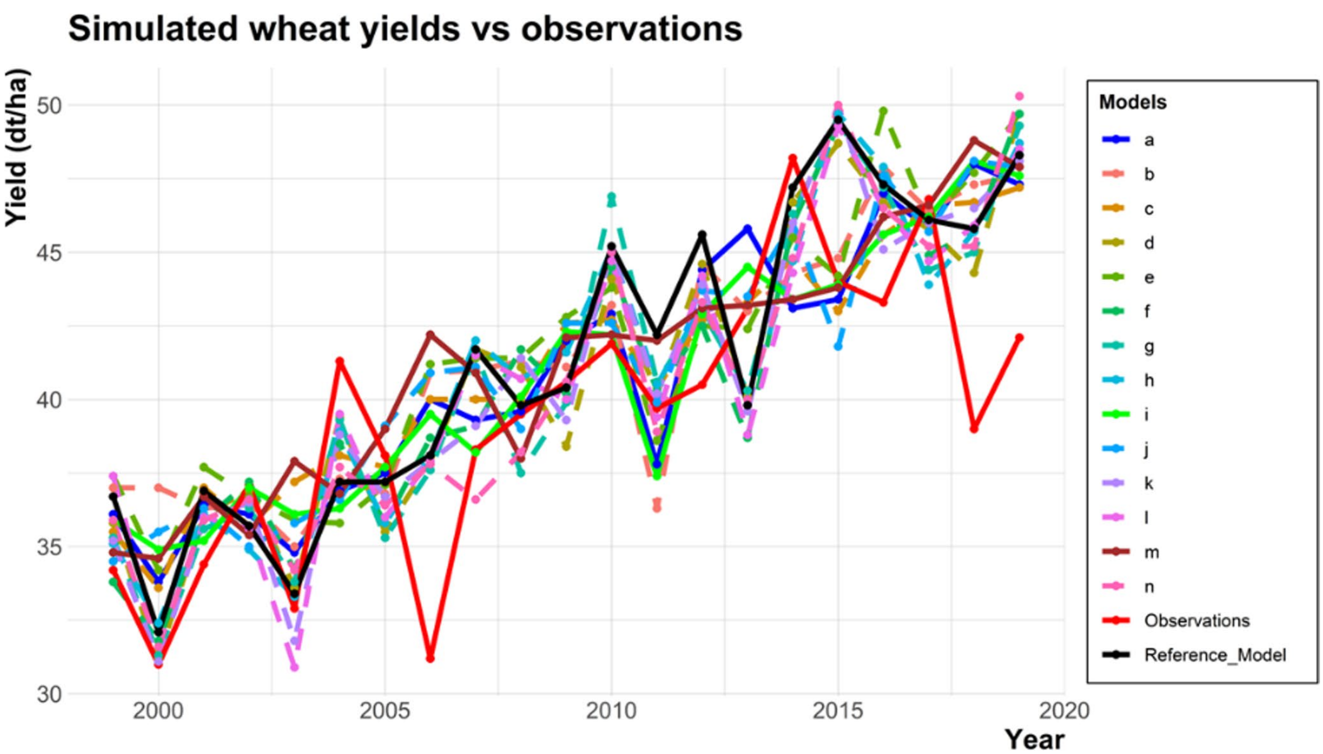
Table 2 Model performance in country-average wheat and sugar beet yield prediction for all configurations

Configuration	Inputs				Wheat R^2	Wheat RMSE	Sugar Beet R^2	Sugar Beet RMSE
a	SPEI				0.50	3.76	0.66	62
b	SPEI	SPI			0.45	4.03	0.70	57
c	SPEI		SMI		0.59	3.38	0.65	63
d	SPEI			Weather data	0.66	3.34	0.60	72
e	SPEI	SPI	SMI		0.45	4.27	0.76	51
f	SPEI	SPI		Weather data	0.60	3.52	0.68	65
g	SPEI		SMI	Weather data	0.63	3.48	0.65	67
h	SPEI	SPI	SMI	Weather data	0.58	3.63	0.64	69
i		SPI			0.49	3.66	0.70	57
j		SPI	SMI		0.48	3.92	0.76	51
k		SPI		Weather data	0.65	3.35	0.68	65
l		SPI	SMI	Weather data	0.58	3.59	0.60	71
m			SMI		0.39	4.23	0.77	50
n			SMI	Weather data	0.58	3.55	0.68	64
Reference				Weather data	0.63	3.65	0.64	69

all provinces, with only two exceptions: Masovian voivodship (wheat) and Silesian voivodship (sugar beet).

According to Fig. 9, the reference configuration captures the overall trend in wheat and sugar beet yields, and the simulated yields are within a reasonable range. The average wheat yield for the reference configuration is 39.2 dt/ha (502.9 dt/ha for sugar beet).

One of the valuable outputs of ABSOLUT is the features used in the regression equations. These are available for each sub-unit and each year. Figure 10 shows the most frequent features (i.e., number of occurrences) in the selected configurations. According to Fig. 10, the aggregated difference between the maximum and minimum temperatures in May and June (dif0506) is the most frequent feature among the other features (337 regressions with four features) for wheat yield simulations under the reference configuration. In general, features based on temperature and solar radiation variables rank highest for wheat. The aggregated June-August maximum temperature (max0608) is the most frequent feature in sugar beet yield simulations. In addition to several features based on temperature and solar radiation, average precipitation from March to April (pcp0304) plays a significant role in crop yield simulations.



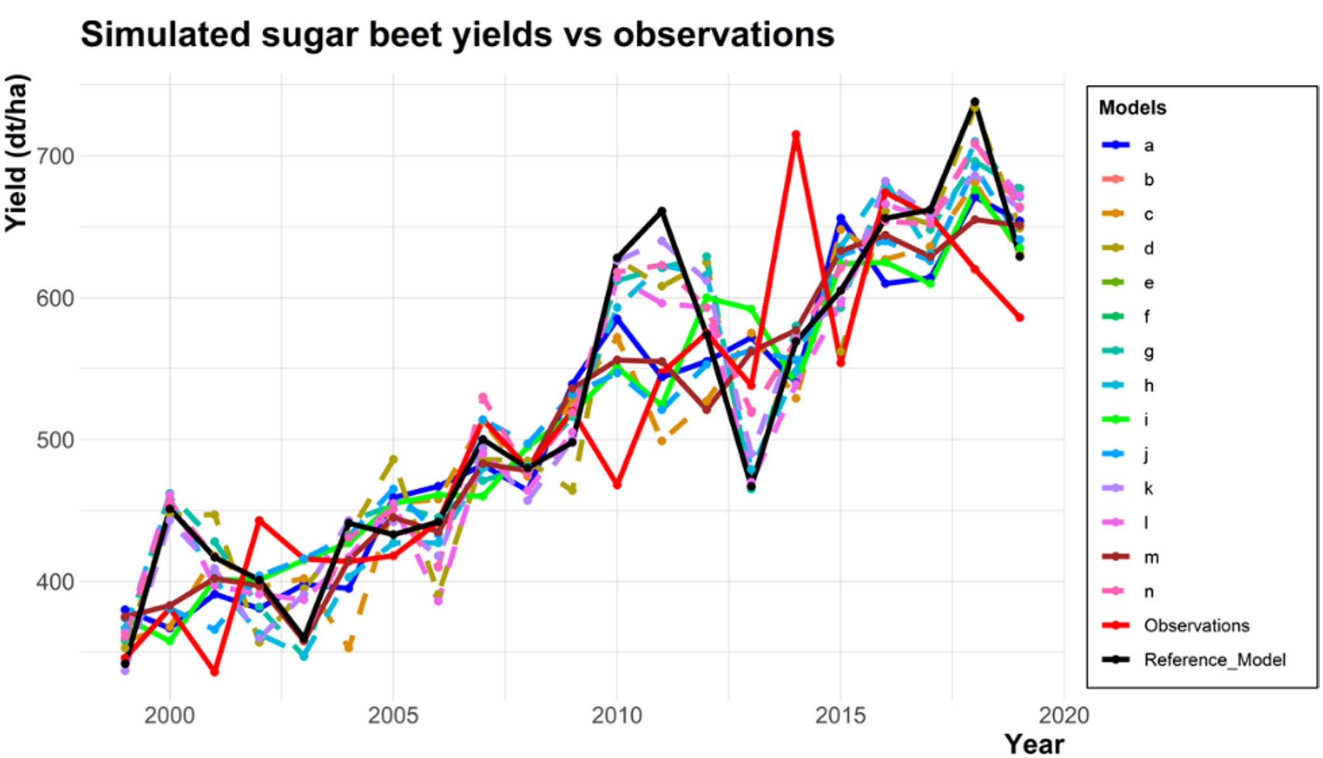


Fig. 8 Simulated and observed wheat and sugar beet yields for the period 1999–2019 over Poland; letters (a-n) correspond to the configurations defined in Table 1 (e.g., a: only SPEI, i: only SPI, m: only SMI, Reference configuration: only weather datasets)

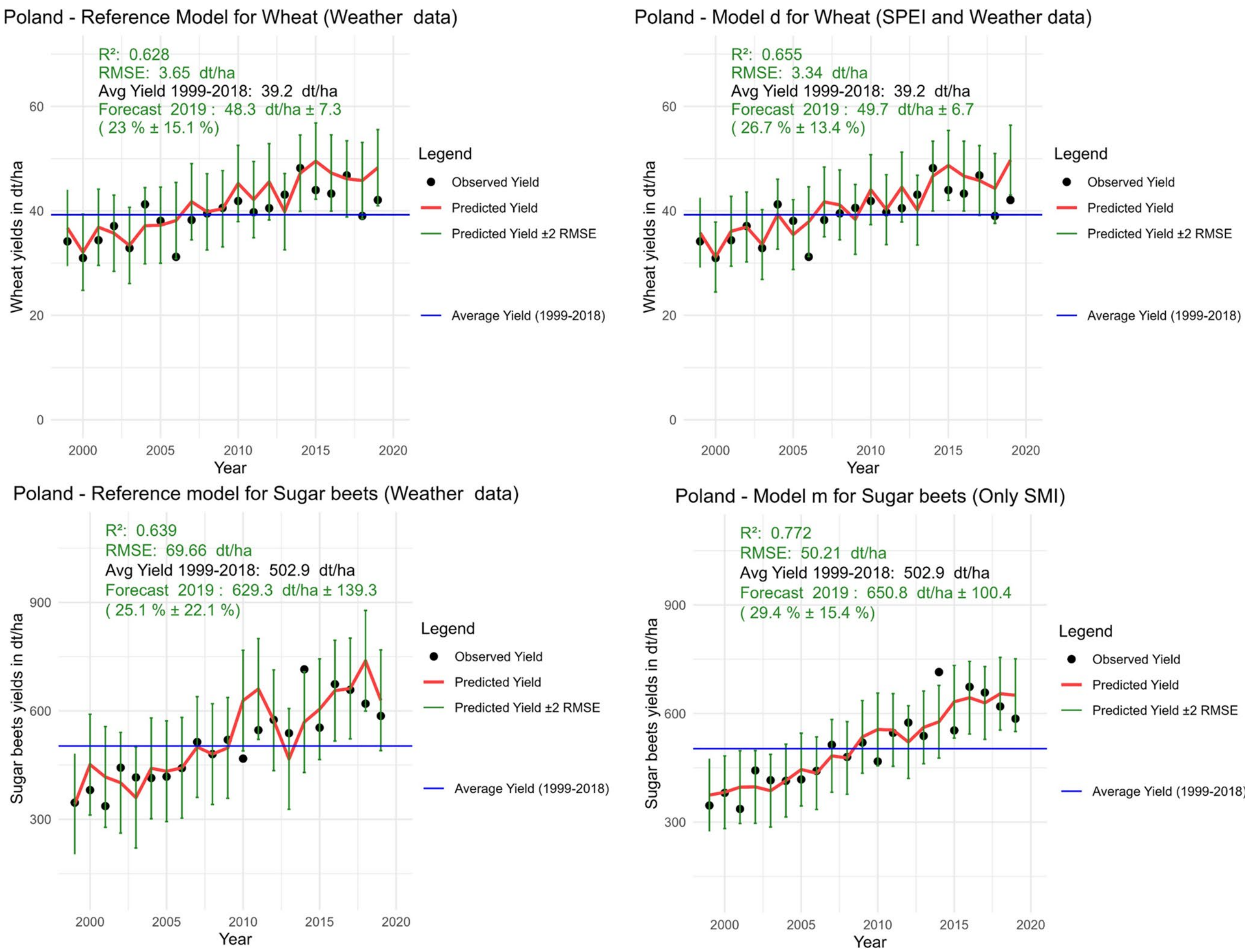


Fig. 9 Simulated wheat and sugar beet yields according to the reference configuration and best configurations in Poland

3.3 Using drought indicators and weather data in crop yield simulations

SPEI-3, SPEI-6, SPEI-9, and SPEI-12 were added as input features, along with the weather datasets, for wheat yield simulations in configuration d. Results for the configuration's 2019 forecasts are presented in Table 4. Based on this configuration, Subcarpathian and Podlaskie have the lowest RMSE for wheat yield simulation (~2.2 dt/ha). The average RMSE is 4.3 dt/ha, and the average simulated yield is 47.7 dt/ha, which is ~5 dt/ha higher than the observed yield in 2019. As in the reference configuration of wheat yield simulations, the most influential features are those in the weather variable group. Still, the aggregated SPEI-6 for August to January and from April to June are also found among the most frequently used features (Fig. 10). Also, for this configuration, Fig. 9 presents predictions for all years, and it can be concluded that it is also accurate.

In the case of sugar beet, the configuration using SMI-3, SMI-6, SMI-9, and SMI-12 (configuration m) shows higher accuracy than the other configurations (Table 4). This configuration shows the lowest RMSE (dt/ha) values in Lublin (42.1 dt/ha). Conversely, regions like Podlaskie and Silesian exhibit high RMSE values of 157.5 dt/ha and 132.9dt/ha, respectively, indicating substantial prediction errors. When considering absolute error, Podlaskie has the largest value (325.3 dt/ha), indicating a significant overestimation of simulated sugar beet yields. In contrast, Silesian shows the smallest absolute error (15.8 dt/ha). Overall, the configuration overestimates sugar beet yields across many voivodeships, with substantial deviations in regions like Podlaskie and Lesser Poland.

Figure 9 shows the performance of ABSOLUT for predicting sugar beet yields in Poland based on configuration m (only SMI) and the reference configuration. The configuration using only SMI shows a higher fit to the observed data, suggesting that soil moisture is a strong predictor for sugar beet yield in this region. It has a more consistent trend closely aligned with observed yields, and the predictions fall within a narrower confidence range, indicating greater

Table 3 The weather-based reference configuration accuracy in predicting wheat and sugar beet yields in 2019 for each voivodship (unit for yield, RMSE, and Absolute error: dt/ha)

Voivodeship	Wheat				
	Year	Observations	Simulated	RMSE	Absolute error
Lower Silesian	2019	47.1	54.3	4.04	7.20
Kuyavian-Pomeranian	2019	44.8	50.1	4.71	5.34
Łódź	2019	34.6	39.7	4.27	5.11
Lublin	2019	47.5	50.4	4.41	2.94
Lubusz	2019	35.4	40.7	7.55	5.33
Lesser Poland	2019	38.5	39.8	3.12	1.33
Masovian	2019	34.9	34.3	4.36	0.60
Opole	2019	60.2	62.7	6.77	2.48
Subcarpathian	2019	36.9	41.8	2.35	4.94
Podlaskie	2019	30.0	36.0	2.94	6.02
Pomeranian	2019	52.9	56.3	4.69	3.43
Silesian	2019	42.9	51.8	3.97	8.92
Holy Cross	2019	33.1	38.2	3.54	5.11
Warmian-Masurian	2019	46.1	50.5	3.65	4.42
Greater Poland	2019	41.3	47.1	4.78	5.82
West Pomeranian	2019	47.0	48.7	6.88	1.72
	Sugar beet				
Voivodeship	Year	Observations	Simulated	RMSE	Absolute error
Lower Silesian	2019	562	604	79.2	42.2
Kuyavian-Pomeranian	2019	566	608	93.8	41.9
Łódź	2019	589	630	134	41.6
Lublin	2019	534	579	57.2	44.3
Lubusz	2019	582	666	148	83.7
Lesser Poland	2019	636	803	140	167
Masovian	2019	533	691	75.1	158
Opole	2019	636	691	126	55.1
Subcarpathian	2019	638	675	133	37.0
Podlaskie	2019	286	540	155	254
Pomeranian	2019	742	791	52.0	49.0
Silesian	2019	701	651	148	50.1
Holy Cross	2019	609	661	96.5	51.7
Warmian-Masurian	2019	609	717	54.5	108
Greater Poland	2019	567	593	103.8	25.6
West Pomeranian	2019	582	645	142.1	62.8

precision. In contrast, the weather-based reference configuration shows a less stable trend, with larger fluctuations in predicted sugar beet yields, suggesting that including weather variables introduces greater variability in the predictions. This configuration also exhibits a wider range of prediction errors, as shown by the larger error bars. Consequently, while the weather-based configuration may account for a broader range of environmental factors, its predictions appear to be less accurate and precise than those of the SMI-based configuration. This difference highlights the importance of soil moisture drought indicators, particularly in modelling sugar beet yield relative to general weather data. As seen in Fig. 10, the short-term soil moisture drought indicator (SMI-3) has the strongest effect on the results. It was observed that the three-month accumulation period for SMI was the most frequent (i.e., the top-selected features). In addition, SMI for the period from April-July to August occurs very frequently (5 times among the top 6 features). This coincides with the first part of the sugar beet growing period. Moreover, the top feature in the SMI-based configuration is the period from September to February. It slightly coincides with the last growth phase before harvest (usually September-October).

Regarding the specific indicators selected by the ABSOLUT simulator, the model did not apply a single universal timescale. Instead, it identified the most relevant accumulation periods for each province. As shown in Fig. 10, short-term soil moisture indicators (SMI-1 and SMI-3) were most frequently selected for sugar beet during the summer months, while wheat showed a higher dependency on intermediate SPEI scales (SPEI-3 and SPEI-6) during the spring growth phase.

4 Discussion

The current study provides a comprehensive evaluation of the role of drought indicators in enhancing statistical crop yield prediction models through sequential hybridization, using Poland as a case study. The results align with existing literature on the potential of combining process-based (i.e., SWAT) and statistical models (i.e., ABSOLUT).

4.1 Enhanced model accuracy through hybridization

Integrating SPEI and SMI into the ABSOLUT statistical model demonstrated significant improvements in accuracy compared to weather-only configurations. This is consistent with findings by Dong et al. (2023) and Li et al. (2023), who showed that hybrid models incorporating biophysical metrics enhance the reliability of hydrological and agricultural predictions. However, this study highlights how SPEI better captures wheat yield variability during extreme droughts, such as the 2018 event in Poland, compared to SPI. This aligns with Vicente-Serrano et al. (2010), who emphasized the added value of incorporating potential evapotranspiration in drought metrics. Like the current study, Khan et al. (2021) modeled cotton and wheat yields and showed a

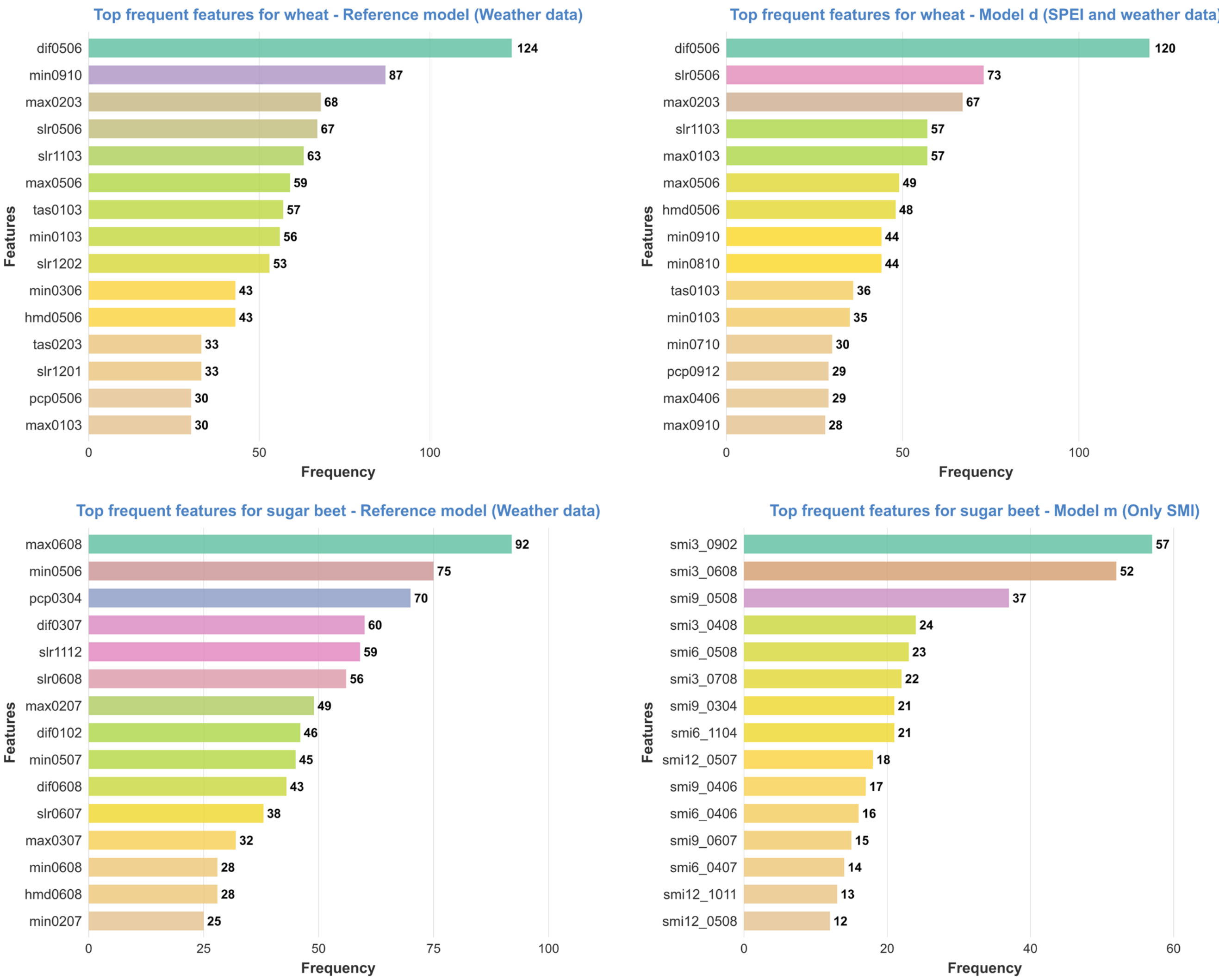


Fig. 10 The most frequent features (i.e. number of occurrences) in selected regression for simulating wheat and sugar beet yields - The feature names consist of variable acronyms (tas = mean temperature, pcp = precipitation, slr = solar radiation, hmd = humidity, dif = difference between max and min temperature, min = minimum temperature, max = maximum temperature) and two-digit numbers of the start and end months of their time aggregation

significant relationship between wheat yield and the SPEI in Pakistan using Random Forest (RF) and Yao et al. (2022) highlighted that the SPEI index correlates more with maize yield than the agricultural drought index SMDI (soil moisture deficit index). In another research by (Clarke et al., 2021), it was concluded that combining drought severity indicators (DSI) adds hydro-meteorological knowledge to crop modelling approaches and offers more robust results, consistent with our findings.

4.2 Role of soil moisture in root crop simulations

The superior performance of the SMI-only configuration for sugar beet, compared to the SPEI-based configurations for wheat, reflects the distinct physiological requirements of these crops. Sugar beet, as a root crop, is directly dependent on the moisture content of the soil profile throughout the tuber expansion phase. SMI provides a direct measure of this available water. In contrast, wheat yields are often more sensitive to the atmospheric water balance (precipitation versus evapotranspiration) during critical reproductive stages, such as anthesis, which is more holistically captured by the SPEI.

For sugar beet, the SMI-only configuration indicates that soil moisture is a dominant driver of yield variability. This result supports Modanesi et al.'s (2020), Jones et al. (2003) and Żarski et al. (2020) research. Modanesi et al. (2020) demonstrated the strong predictive power of soil moisture metrics for wheat and maize in India with different climatic conditions than the current study. Similar to our results, the effect of SMI in August and September on crop yield is described in Peichl et al. (2018). Moreover, the current

Table 4 The selected configuration accuracy in predicting wheat and sugar beet yields in 2019 for each province based (unit for yield, RMSE, and Absolute error: dt/ha)

Voivodeship	Wheat				
	Year	Observations	Simulated	RMSE	Absolute error
Lower Silesian	2019	47.1	54.3	4.50	7.20
Kuyavian-Pomeranian	2019	44.8	55.2	4.20	10.4
Łódź	2019	34.6	41.8	4.20	7.20
Lublin	2019	47.5	50.3	4.50	2.80
Lubusz	2019	35.4	40.2	7.70	4.80
Lesser Poland	2019	38.5	39.7	3.70	1.20
Masovian	2019	34.9	35.8	3.50	0.90
Opole	2019	60.2	65.0	5.00	4.80
Subcarpathian	2019	36.9	41.0	2.20	4.10
Podlaskie	2019	30.0	36.0	2.10	6.00
Pomeranian	2019	52.9	62.5	4.80	9.60
Silesian	2019	42.9	50.3	4.50	7.40
Holy Cross	2019	33.1	38.7	3.90	5.60
Warmian-Masurian	2019	46.1	53.0	4.00	6.90
Greater Poland	2019	41.3	47.1	4.30	5.80
West Pomeranian	2019	47.0	51.7	5.70	4.70
	Sugar beet				
Voivodeship	Year	Observations	Simulated	RMSE	Absolute error
Lower Silesian	2019	562.2	638	84.4	76.2
Kuyavian-Pomeranian	2019	566.3	658	60.9	91.9
Łódź	2019	588.9	606	75.6	16.9
Lublin	2019	534.4	612	42.1	77.8
Lubusz	2019	582.4	621	98.4	38.6
Lesser Poland	2019	635.9	757	125	121
Masovian	2019	533.4	669	62.0	135
Opole	2019	636.1	720	99.9	83.6
Subcarpathian	2019	638.3	732	99.0	94.1
Podlaskie	2019	285.8	611	158	325
Pomeranian	2019	742.1	684	71.6	57.8
Silesian	2019	701.4	686	133	15.8
Holy Cross	2019	609.0	694	77.4	84.5
Warmian-Masurian	2019	609.4	640	60.7	30.9
Greater Poland	2019	567.2	618	74.5	50.6
West Pomeranian	2019	582.3	716	60.8	133

study adds more details by showing that short-term SMI (e.g., three-month accumulation periods) is particularly significant during the early growing stages of sugar beet, similar to Freckleton et al. (1999) that showed average temperature and precipitation during July and August and mean temperature during April were highly correlated with sugar beet yields.

4.3 Regional variability in model performance

The study also reveals substantial spatial variability in model performance across Poland's voivodeships, a finding supported by Hu et al. (2024), who noted that localized climatic and soil conditions significantly influence model outputs. The observed spatial variance in model accuracy, exemplified by the sugar beet RMSE ranging from 42.1 dt/ha in Lublin to 157.5 dt/ha in Podlaskie, can be further explained by the regional agricultural characteristics shown in Fig. 4. This variability underscores the importance of regional calibration, as highlighted by Jin et al. (2018), to improve the applicability of crop yield models across diverse agro-climatic zones. A comparative analysis suggests that the model's reliability is closely linked to cultivation density and historical yield stability:

- High-Performing Regions: In voivodeships like Lublin, which feature high cultivation area density and consistently high historical yields, the statistical model benefits from a stronger signal-to-noise ratio in the aggregated provincial data.
- Lower-Performing Regions: In regions such as Podlaskie, where sugar beet cultivation is less dense and

historical yields are lower, the regional average is more sensitive to localized factors (e.g., specific farm management or soil micro-variations) that are not fully captured by the broad SMI or SPEI indicators.
- The average meteorological data from the voivodships were used in the model setup; however, the spatial distribution of crop lands in Podlaskie is in the southwest, which could increase noise in the results.

This suggests that while the sequential hybridization significantly improves yield reliability overall, its application is most effective in primary agricultural regions where the crop-specific response to hydro-climatic variables is more pronounced and statistically representative.

It is noteworthy that the hybridized model's performance in the 2019 spatial validation (Table 4) exhibited greater heterogeneity across provinces compared to its long-term historical average (Table 2). While sequential hybridization enhances overall model reliability over the two-decade study period, its predictive advantage in a specific year like 2019 may converge with the reference model in regions where moisture was not the primary limiting factor for yield. This suggests that the 'added value' of SWAT-derived indicators is most pronounced during periods of significant hydro-climatic stress. In climatically typical years, standard meteorological data remain robust predictors; however, the integration of SMI and SPEI serves as a critical 'buffer,' allowing the model to maintain structural stability and accuracy when drought conditions deviate from historical weather-yield norms. Accordingly, the detailed spatial analysis for 2019 should be interpreted as an illustrative assessment of regional sensitivity rather than as a replacement for the multi-year performance metrics presented in Sect. 3.1.

4.4 Limitations of weather-only configurations

The study's findings support the limitations of weather-only configurations, which, while robust for baseline predictions, fail to account for slight factors such as drought stress. This was also observed in Germany for silage maize predictions by Peichl et al. (2018). Similar conclusions were obtained by Prodhan et al. (2022) and Hu et al. (2024), who emphasized that relying entirely on weather data limits configuration sensitivity to critical environmental drivers, such as soil moisture, extreme weather conditions, and evapotranspiration.

4.5 Future directions

The findings also open avenues for further research. Additional environmental factors, such as remote sensing data on vegetation health or real-time soil moisture levels, could enhance model flexibility. The potential to extend this hybrid modeling approach to other crops and regions globally warrants exploration, as Zhu et al. (2022) emphasized in the context of global warming impacts on agriculture.

A limitation of this approach is that administrative voivodeships do not necessarily correspond to homogeneous agroclimatic or soil regions. Each voivodeship may include contrasting soil types, crop-management systems, and local hydroclimatic conditions. This can introduce noise into the statistical relationship between predictors and observed yields, especially in regions where the target crop occupies only part of the voivodeship or where production is concentrated in specific subregions. The relatively weak performance for sugar beet in Podlaskie illustrates this issue. Future applications of the hybrid ABSOLUT framework could benefit from agrometeorological or agroecological regionalization, provided that reliable yield statistics and crop-area data are available at such spatial units.

Another important limitation is that agrotechnical factors were not explicitly included in the current modelling framework. Yield levels are influenced by fertilization, crop varieties, sowing and harvest dates, pest and disease control, irrigation, drainage, and farm-management intensity. These factors may explain part of the residual error, particularly in regions where observed yields are strongly affected by local management rather than by climatic or soil-moisture variability alone. Therefore, the present results should be interpreted as the contribution of weather and drought-related predictors to yield modelling, rather than as a complete representation of all agronomic controls on yield.

5 Conclusion

This study underscores the significant improvement in crop yield prediction accuracy achieved by integrating drought indicators with weather datasets using the ABSOLUT model at the voivodeship level in Poland. By adopting a sequential hybridization approach, we demonstrated that configurations leveraging SPEI for wheat and SMI for sugar beet outperformed weather-only configurations. These findings support our hypothesis that drought indicators enhance the predictive power and robustness of crop yield statistical models by providing critical insights into moisture variability.

The regional calibration of configurations across Poland's voivodeships highlighted the importance of localized climatic and agricultural conditions in determining model performance. This regional variability underscores the need for tailored yield-prediction approaches, particularly in regions prone to climatic extremes. Because the hybridization framework relies on generic drought indicators derived from widely used hydrological models, the proposed approach is readily transferable to other regions and crops, provided suitable yield statistics are available. Finally, this research contributes to the broader goal of developing resilient agricultural systems by providing tools that support better decision-making under changing climatic conditions. By advancing the integration of process-based insights with data-driven approaches, this study paves the way for more reliable and robust crop yield simulations in the face of global climate change.

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Author contributions T.C.; M.P., M.R.E.: writing and editing the main text; M.R.E.: software and analyses; T.C. and M.P.: supervising.

Data availability The data used in this study are publicly accessible from the 4TU Centre for Research Data in NetCDF and TIF formats at https://figshare.com/articles/dataset/G2DC-PL_A_gridded_2_km_daily_climate_dataset_for_the_union_of_Polish_territory_and_the_Vistula_and_Odra_basins/12764888 (last access: 17 May 2026).

Declarations

Competing interests The authors declare no competing interests.

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