Received: 16 August 2024 | Accepted: 17 March 2025

DOI: 10.1002/agj2.70059

Agronomy Journal

ORIGINAL ARTICLE

Agronomy, Soils, and Environmental Quality

# Environment and not genotype drives soybean yield stability in Northern Germany

**Richard Ansong Omari**[1,2] | **Mosab Halwani**[1] | **Moritz Reckling**[1,3] | **Ma Hua**[4] | **Sonoko D. Bellingrath-Kimura**[1,2]

[1]Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany

[2]Faculty of Life Sciences, Humboldt-University of Berlin, Berlin, Germany

[3]Department of Crop Production Ecology, Swedish University of Agricultural Sciences (SLU), Uppsala, Sweden

[4]School of Life Sciences, Chongqing University, Chongqing, China

**Correspondence**

Richard Ansong Omari, Leibniz Centre for Agricultural Landscape Research (ZALF), Land Use and Governance, Eberswalder str. 84, 15374, Müncheberg, Germany.

Email: Richard.Omari@zalf.de.

Assigned to Associate Editor Paulo Ribeiro.

**Funding information**

SusCrop-ERA-NET, Grant/Award Number: 031B0807B; BMBF, Bioökonomie International, Grant/Award Number: 031B1212

**Abstract**

Soybean [*Glycine max* (L.) Merr.] is a major plant protein source worldwide, and its cultivation in central and northern Europe is still emerging. To understand the influence of the environment in the northern latitudes and its interactions with different soybean genotypes, a 3-year multi-location trial was carried out in Northern Germany. The objectives were to (i) quantify the grain yield and stability of six soybean genotypes across eight environments using the additive main effect and multiplicative interaction and best linear unbiased prediction models to identify superior genotypes as well as optimal environmental conditions for growing soybeans in northern latitudes, and (ii) assess the genotype-environment interaction on soybean grain yield, crude protein, and protein yield to explore the factors contributing to yield variability. The mean soybean grain yield was 2060 kg ha$^{-1}$, and it varied among locations and across years. A large portion of the total variance in all parameters was explained by environment (67.6%–82.8%), followed by genotype-environment interaction (7.7%–14.6%), while a small portion was attributed to genotypes (1.3%–10.5%). The growing conditions at site Müncheberg produced a stable soybean yield but were less productive than sites Dahlem and Dedelow. Regular precipitation in July and August corresponded with increased grain yield. The stability models ranked the feed-grade cultivar Merlin as superior in terms of stability and performance. In contrast, the food-grade cultivar Comandor may be risky for grain production in rainfed conditions. The study highlighted soybean's agronomic potential in northern latitudes and the influence of the prevailing environment on yield and stability.

**Abbreviations:** AMMI, additive main effect and multiplicative interaction; ASTAB, AMMI-based stability parameter; ASV, AMMI stability value; BLUP, best linear unbiased prediction; DM, dry matter; GDD, growing degree days; GEI, genotype-environment interaction; GSI, genotype stability index; HMGV, harmonic means of genotypic value; HMRPGV, harmonic mean of relative performance of genotypic value; IPCA, interaction principal component axis; MASI, modified AMMI stability index; MG, maturity group; RPGV, relative performance of genotypic value; WAAS, weighted average of absolute scores; WAASBY, weighted average of weighted average of absolute score.

# 1 | INTRODUCTION

Due to concerns about the European Union's (EU) reliance on protein imports and associated environmental repercussions, expanding domestic protein crop production is one important aim of the EU protein strategy (Albaladejo Román, 2023). The EU relies on imports of high-protein animal feed, particularly from soybeans to meet the demands of the livestock industry (Boerema et al., 2016; Karlsson et al., 2021). This is because its domestic production covers only 6% of the total soybean and soybean [*Glycine max* (L.) Merr.]-derived products consumed (EUROStat, 2021). There is thus the need to expand soybean production to areas with suitable climates and conditions for cultivation.

Climate change will affect agricultural production in drought-prone areas (Gudmundsson & Seneviratne, 2016; Li et al., 2009). Elevated temperature has been predicted to impact the reproductive development and yield of soybeans (Köhler et al., 2019; Korres et al., 2016). However, an increase in temperature is expected to lengthen the growing season in the northern hemisphere, which may likely favor the growth of heat-tolerant crops such as soybean (Kühling et al., 2018; Tchebakova et al., 2011). The impacts of climate change along with the breeding of early maturing genotypes may allow the cultivation of soybeans in central and northern Europe, which are non-traditional growing areas (Nendel et al., 2023).

Soybean cultivation is relatively new in a large part of Europe, and there is a growing interest among growers, researchers, policymakers, and other stakeholders to expand its cultivation area. Northern Germany is Europe's new frontier for soybean cultivation (Karges et al., 2022), and there are attempts to incorporate the crop into the cropping system in the region (Halwani et al., 2019; Reckling et al., 2020). Similarly, Yuan et al. (2020) isolated and Omari et al. (2022) tested promising indigenous soybean rhizobia for increasing grain yield in drought-prone areas in Northern Germany. While drought presents one of the major limitations to soybean production in these areas, Karges et al. (2022) showed the agro-economic potential of cultivating the crop with artificial irrigation.

Selection of suitable soybean genotypes that show high yield performance and high adaptability to a wide range of environments is important for the grower and breeder (Ito et al., 2016; Olivoto et al., 2019). These adaptable characters are not only associated with inherent genotypic traits but also with management and environmental variables and their multiple interactions affecting yields (Chenu et al., 2011; Picasso et al., 2019). Grain yield performance and stability in legumes are particularly important in Europe because farmers and grower organizations are often concerned about their high yield variability (Zimmer et al., 2016), although Reckling et al. (2018) showed that grain legume yields are as reliable as those of other spring-sown crops in major northern European production systems. To expand soybean production further, multi-environmental trials are needed to identify stable and adaptable cultivars for optimizing the agronomic and economic benefits, as well as the effects of food characteristics. Karges et al. (2022) evaluated the grain yield, stability, effect of irrigation, and agro-economic performance of three soybean cultivars in one site in Northern Germany. Their study was, however, limited by the number of locations and cultivars.

To assess yield performance, various methods are available, and the use of a combination of methods is suggested to avoid biased conclusions (Reckling et al., 2021). Additive main effect and multiplicative interaction (AMMI) and best linear unbiased prediction (BLUP) are widely used models for decoding genotype-environment interactions (GEI) in several crop species in multi-environmental trials. While the AMMI is mainly used in a fixed-effect model framework, BLUP employs mixed linear models to predict the GEI pattern from random error (Olivoto et al., 2019). The AMMI has graphical tools for modeling GEI and has successfully been used to facilitate the selection of promising genotypes in different crop species (Bocianowski, Niemann, et al., 2019; Bocianowski, Warzecha, et al., 2019; Hakl et al., 2019; Ito et al., 2016). However, it fails to accommodate a linear mixed-effect model structure and retains most of the random error in the last interaction principal component axis (IPCA), unlike the BLUP, which employs all the estimated IPCA axes for enhanced model predictive accuracy (Olivoto et al., 2019).

The objectives of the present study were to (i) quantify the grain yield and stability of six soybean genotypes across eight environments (three sites and 3 years) using the AMMI and BLUP models to identify superior genotypes as well as optimal environmental conditions for growing soybean in northern latitudes, and (ii) to assess the GEI influence on soybean grain yield, crude protein, and protein yield to explore the influencing factors contributing to yield variability.

# 2 | MATERIALS AND METHODS

## 2.1 | Site description

The study was carried out from 2019 to 2021 at three locations in Northern German: the experimental station of the Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg; experimental station of the Humboldt Universität zu Berlin, Dahlem; and the ZALF research station located in Dedelow.

The research station in Müncheberg (52°31′ N, 14°07′ E) is located 51 km east of Berlin, and its soil type is sandy loam with a high spatial heterogeneity. Total soil nitrogen (N) (0- to 30-cm soil depth) ranged from 0.7 to 0.8 g $kg^{-1}$, total carbon from 5.1 to 6.4 g $kg^{-1}$, and soil pH (KCl) from 6.1 to

TABLE 1 Characteristics of the tested soybean genotypes.

| Cultivar | Code | Date of registration | Maturity group | Early growth | Height | Growth type | 1000-Grain weight | Grain protein content |
|---|---|---|---|---|---|---|---|---|
| Siroca | G1 | 2017 | 00 | 6 | 4 | Semi-determinate | 5 | 6 |
| Merlin | G2 | 1997 | 000 | 7 | 3 | Indeterminate | 1 | 4 |
| Sultana | G3 | 2009 | 000 | 5 | 3 | Semi-determinate | 5 | 6 |
| Shouna | G4 | 2014 | 00 | – | 5 | Indeterminate | 3 | 5 |
| Tofina | G5 | 2019 | 000 | 6 | 4 | Semi-determinate | 8 | 7 |
| Comandor | G6 | 2016 | 000 | – | 5 | Semi-determinate | 4 | 5 |

*Note*: German descriptive variety list (Bundessortenamt, 2021) for cv. Comandor and cv. Shouna and Austrian descriptive variety list (BAES, 2025) for all other cultivars and growth type from the variety list of the German Soybean Association (2021). The rating scale ranges from 1 to 9 according to the German federal plant variety office (BSA) with 1 indicating low and 9 denoting high for initial vegetative development, height, 1000-grain weight, and grain protein content. For the MG ratings, 000 represents early while 00 are later maturing cultivars.

6.9. The site has a mean annual precipitation of 563 mm and a mean long-term annual temperature of 9.0˚C. The soil at the Dahlem research station (52˚28′ N, 13˚18′ E) is characterized as Albic Luvisol (WRB, 2015) and contains on average 71% sand, 23% silt, and 6% clay. Dahlem soil (0–30 cm) contained total soil N in the range of 0.8–1.2 g kg$^{-1}$ and had a soil pH (KCl) between 5.6 and 6.9. Average annual precipitation at the station is 561 mm, and the 30-year average annual temperature is 9.9˚C. The research station at Dedelow (53˚21′55.4″ N, 13˚48′17.7″ E) is located 124 km north of Berlin. The soil at the station is classified as Haplic Luvisol (WRB, 2015), with a texture ranging from loamy sand to sandy loam. The total soil N and soil pH (KCl) at 30-cm depth ranged from 0.9 to 1.7 g kg$^{-1}$ and between 6.2 and 6.6, respectively. The mean annual precipitation at Dedelow is 500 mm, and the 30-year average temperature is 8.8˚C.

## 2.2 | Soybean cultivars

Six commercially available soybean cultivars, namely, Siroca, Merlin, Sultana, Shouna, Tofina, and Comandor were evaluated in this study. Cultivars Merlin, Sultana, Tofina, and Comandor are early maturing of the 000 maturity group (MG), while Siroca and Shouna belong to MG 00. The tested cultivars are of different genetic backgrounds and are commercially available in many parts of Europe. Merlin and Sultana are widely used for animal feed, while Siroca, Shouna, Tofina, and Comandor are also cultivated for food use. Tofina was developed for tofu production. The description of the tested cultivars is summarized in Table 1.

## 2.3 | Trial description

Field experiments were conducted at each experimental station in three consecutive seasons (2019–2021). Soybeans were grown on different fields with no soybean cultivation history at each station in each growing year. All experiments at each site were laid out in a randomized complete block design with four replications. The unit plot size at each site was 36 m$^2$ (3 m by 12 m).

Each location had different preceding crops in each year, as summarized in Table 2. Similar tillage but different weed control practices were used in each site in all 3 years. Weeds were controlled chemically in Dahlem and Dedelow, and mechanically in Müncheberg and Dedelow (Table 2). Seed inoculation procedures, sowing, and harvesting dates were similar among all sites. Commercial rhizobium inoculant (HiStick inoculum) containing high $N_2$ fixing *Bradyrhizobium japonicum* was applied at 400 g inoculant to 100 kg$^{-1}$ seeds a few hours before seeding at all locations. Sowing was done in rows spaced 50 cm apart at a density of 70–80 seeds per m$^2$ at 3- to 4-cm depth in each site following experiences from earlier trials (Karges et al., 2022) and grower recommendations by the German soybean association. Sowing was done when soil temperature was higher than 8˚C–10˚C and the weather conditions were stable for the next 1–2 weeks. Detailed descriptions of planting dates, tillage, crop protection, precipitation, and harvesting are given in Table 2.

## 2.4 | Plant sampling

Soybean plants were harvested mechanically with a plot combine harvester after reaching physiological maturity, when seed moisture was around 14%–15%, 90%–95% of the pods in each plot had achieved their mature brown color, and all leaves had abscised from the soybean plant. Harvesting was done between September 21 and October 7 across sites and years (Table 2). After the final harvest, grain yield (kg ha$^{-1}$) was determined at 86% dry matter (DM), which is the standard DM content in Germany and other countries across Europe. Grain moisture content was determined by oven drying 10 g of

**TABLE 2** Summary of agro-climatic conditions, agronomic history, and agrotechnical practices at each location from 2019 to 2021.

| | | Müncheberg | Dahlem | Dedelow |
|---|---|---|---|---|
| Previous crop | | | | |
| | 2019 | Winter rye | Winter wheat | Rapeseed |
| | 2020 | Winter wheat | Winter wheat | Barley |
| | 2021 | Winter wheat | Winter triticale | Maize |
| Soil tillage | | | | |
| | 2019 | Ploughing on Mar. 28, 2019, and cultivator on May 8, 2019 | Ploughing on Apr. 29, 2019, and cultivator on May 8, 2019 | Ploughing on Mar. 29, 2019, and cultivator on Apr. 11, 2019 |
| | 2020 | Ploughing on Mar. 13, 2020, and cultivator on May 4, 2020 | Ploughing on Nov. 11, 2019, and cultivator on May 18, 2020 | Ploughing on Apr. 3, 2020, and cultivator on Apr.15, 2020 |
| | 2021 | Ploughing on Mar. 24, 2021, and cultivator on May 17, 2020 | Ploughing on Apr. 1, 2021, and cultivator on May 10, 2021 | Ploughing on Apr. 13, 2021, and cultivator on Apr. 28, 2021 |
| Sowing | | | | |
| | 2019 | May 2, 2019 | May 9, 2019 | Apr. 29, 2019 |
| | 2020 | Apr. 28, 2020 | May 18, 2020 | Apr. 23, 2020 |
| | 2021 | May 11, 2021 | May 10, 2021 | May 5, 2021 |
| Weed control | 2019 | Mechanical weeding with harrow and hoe | Herbicide Sencor liquid on May 16, 2019 | Herbicide Stomp Aqua on Apr 30, 2019. (Clearfield Clentiga on May 29, 2019 |
| | 2020 | Mechanical weeding with harrow and hoe | Herbicide Roundup PowerFlex on May 12, 2020, Clearfield Clentiga on May 29, 2020, and Fusilade Max on June 12, 2020 | Mechanical weeding with hand hoe on May 27, 2020, July 09, 2020, and August 10, 2020 |
| | 2021 | Mechanical weeding with harrow and hoe | Herbicide Clearfield Clentiga on May 26, 2021, and Fusilade Max on June10, 2021 | Mechanical weeding with hoe on June 7, 2021, July 9, 2021, and Aug. 10, 2021 |
| Total precipitation from sowing to harvesting (in mm) | | | | |
| | 2019 | 321 | 282 | 313 |
| | 2020 | 295 | 256 | 275 |
| | 2021 | 276 | 325 | 427 |
| Average temperature from sowing to harvesting (in˚C) | | | | |
| | 2019 | 16.5 | 17.8 | 16.2 |
| | 2020 | 15.9 | 17.7 | 15.6 |
| | 2021 | 15.9 | 17.3 | 15.8 |
| Harvest date | | | | |
| | 2019 | Sept. 23, 2019 | Sept. 26, 2019 | NA |
| | 2020 | Sept. 21, 2020 | Sept. 24, 2020 | Sept. 22, 2020 |
| | 2021 | Oct. 7, 2021 | Oct. 1, 2021 | Sept. 20, 2021 |

*Note*: NA: Harvesting could not be done at Dedelow in 2019 due to significant weed infestation and extensive rodent damage.

soybean subsamples at 70˚C to a constant weight. The moisture content value was then used to set the grain yield to 14% moisture content. Crude protein content (%) and crude protein yield (kg ha$^{-1}$) were determined at 100% DM. To determine the crude protein content, three soybean subsamples from each plot harvest were first milled to a sieve size of 1 mm, from which a representative portion of 5 g was analyzed for N using Kjeldahl digestion method and flame photometry (AAS-iCE 3300, Gallery Plus, ThermoFisher Scientific GmbH Microgenics GmbH, Hennigsdorf). The crude protein content (g $kg^{-1}$) in the grain was derived by using the following equation:

$$\text{Protein content} = \text{N content}\left(\text{g kg}^{-1}\right) \times 6.25 \quad (1)$$

where 6.25 is the conversion factor for protein from N (Krul, 2019).

Grain yield, protein content, and protein yield could not be determined at Dedelow in 2019 due to high weed infestation and severe damage by rodents.

## 2.5 | Data analyses

Grain yield, crude protein content, and crude protein yield data for each location were combined and subjected to AMMI biplot analyses using RStudio (Version 4.1.2, RStudio 2022.02.0 Build 443). Environments were defined as combinations of locations and years. Eight environments were thus considered for analyses of six genotypes using the R script metan developed by Olivoto and Lúcio (2020). The script is publicly available at https://github.com/TiagoOlivoto/metan. Pooled analysis of variance (ANOVA) across environments was performed to determine the variance components of different sources of variation and to detect the presence of GEIs. The GEI was partitioned into IPCA and residuals.

The AMMI model (Gauch, 2013; Zobel et al., 1988) for $i$th genotype in the $j$th environment is given by:

$$Y_{ijr} = \mu + g_j + e_j + b_r\left(e_j\right) + \sum_{n=1}^{k} \lambda_k \alpha_{ik} \gamma_{jk} + p_{ij} \quad (2)$$

where $Y_{ijr}$ is the trait mean of genotype $i$ in environment $j$ for replicate $r$, $\mu$ is the grand mean, $g_j$ is the genotypic mean, $e_j$ is the environmental mean deviations, $b_r(e_j)$ is the effect of the block $r$ within the environment $j$, $r$ is the number of blocks, $k$ is the number of principal components analysis (PCA) axis retained in the model, $\gamma_k$ is the eigenvalue of the PCA axis $k$, $\alpha_{ik}$ and $\gamma_{jk}$ are the genotype and environment PCA scores for axis $k$, and $\rho_{ij}$ is the residual.

Five each of the AMMI and BLUP stability indexes were used to compare the stability of genotypes (Table 3). AMMI stability value (ASV), Modified AMMI stability index (MASI), weighted average of absolute scores (WAAS), AMMI-based stability parameter (ASTAB), and genotype stability index (GSI) are computed with the AMMI model. Lower ASV, MASI, WAAS, and ASTAB values denote a more stable genotype across environments (Ajay et al., 2020).

The GSI is based on the summation of rankings of the mean yield and stability indexes and was calculated according to Farshadfar (2008) in the equation:

$$\text{GSI}_i = \text{RM}_i + \text{RA}_i \quad (3)$$

where $\text{GSI}_i$ is the genotype selection index for $i$th genotype, $\text{RM}_i$ is the rank of trait mean for $i$th genotype, and $\text{RA}_i$ is the rank of the ASV for the $i$th genotype. A lower GSI value shows a desirable genotype with a high mean yield and stability (Ajay et al., 2020).

The harmonic means of genotypic value (HMGV), harmonic mean of relative performance of genotypic value (HMRPGV), relative performance of genotypic value (RPGV), weighted average of absolute score (WAASB), and weighted average of weighted average of absolute score (WAASBY) employ the BLUP based on a mixed-effect model. While HMGV is used to estimate yield and stability, RPGV is used to investigate yield performance and adaptability (de Resende, 2016). HMRPGV employs both functions of HMGV and RPGV to evaluate stability, adaptability, and yield simultaneously (de Resende, 2016).

WAASBY index allows the selection of superior genotypes based on average yield performance and stability, while the WAASB score shows the stability of genotypes across environments. A lower WAASB value denotes a genotype or environment that deviates least from the mean performance. In contrast, genotypes with a higher WAASBY index denote high superiority (Olivoto et al., 2019).

WAASBY is calculated according to Olivoto et al. (2019) in the following equation:

$$\text{WAASBY}_i = \frac{\left(\text{rG}_{i \times} \theta_y\right) + \left(\text{rW}_i \times \theta_s\right)}{\theta_y + \theta_s} \quad (4)$$

where $\text{WAASBY}_i$ is the superiority index for the $i$th genotype, and $\theta_Y$ and $\theta_S$ are the weights for response variable and stability, respectively; $\text{rG}_i$ and $\text{rW}_i$ are the rescaled values for GY and WAASB, respectively. We assigned weights 65 and 35 for the response variables and WAASB, respectively, as in Olivoto et al. (2019). In determining the mean performance, a higher weight of 60 and a lower weight of 40 were assigned to grain yield and crude protein or protein yield, respectively. All AMMI and BLUP-based stability statistics were calculated using the metan package in R.

## 2.6 | Meteorological data

Precipitation and temperature were recorded at each site throughout the experimental period. Meteorological data from each site was obtained from a local weather station. Monthly mean temperature and total precipitation are shown in Figure 1. Growing degree days (GDD), also called heat units, are the accumulated heat units from sowing to harvesting of crops. GDD was calculated using the equation by McMaster and Wilhelm (1997):

$$\text{GDD} = \sum_{1}^{n} \frac{T_{\max} + T_{\min}}{2} - T_{\text{base}} \quad (5)$$

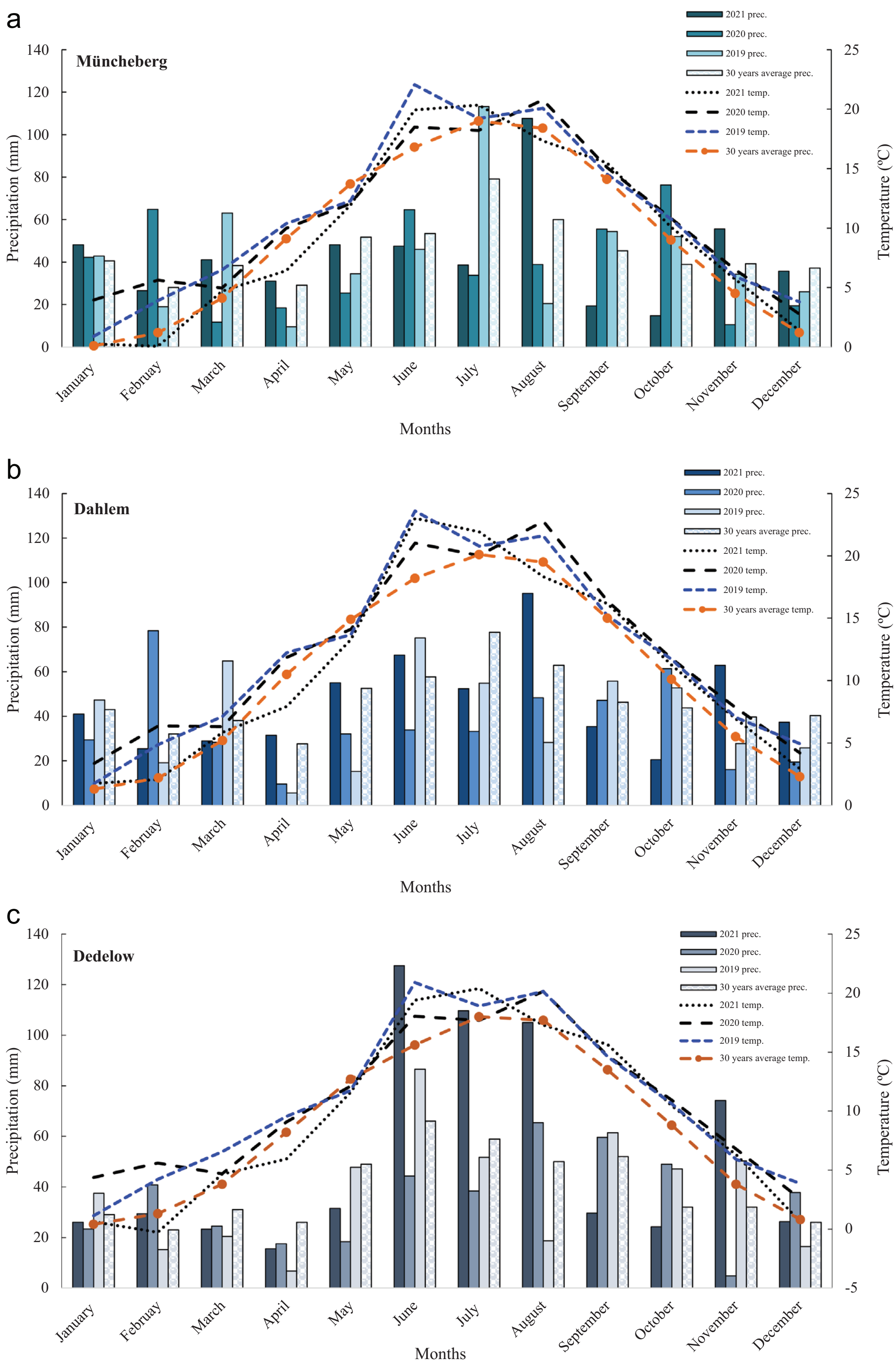


**FIGURE 1** (a) Monthly total precipitation (mm) on the left *y*-axis and monthly average temperature (˚C) on the right *y*-axis in Müncheberg from 2019 to 2021 compared with the long-term 30-year (1990–2020) average. Prec., precipitation; temp., temperature. (b) Monthly total precipitation (mm) on the left *y*-axis and monthly average temperature (˚C) on the right *y*-axis in Dahlem from 2019 to 2021 compared with the long-term 30-year (1990–2020) average. Prec., precipitation; temp., temperature. (c) Monthly total precipitation (mm) on the left *y*-axis and monthly average temperature (˚C) on the right *y*-axis in Dedelow from 2019 to 2021 compared with the long-term 30-year (1990–2020) average. Prec., precipitation; temp., temperature.

**TABLE 3** List of additive main effect and multiplicative interaction (AMMI) and best linear unbiased prediction (BLUP) stability indicators.

| Stability parameter | Abbreviation | Description | Reference |
|---|---|---|---|
| AMMI stability value | ASV | $\text{ASV} = \sqrt{\left[\frac{\text{SS}_{\text{IPCA1}}}{\text{SS}_{\text{IPCA2}}}(\text{IPCA}_1)^2\right] + (\text{IPCA}_2)^2}$ | Purchase et al. (2000) |
| Modified AMMI stability index | MASI | $\text{MASI} = \sqrt{\sum_{n=1}^{N'} \text{PC}_n^2 \times \theta_n^2}$ | Ajay et al. (2020) |
| Weighted average of absolute scores | WAAS | $\text{WAAS} = \frac{\sum_{k=1}^{p} \mid \text{IPCA}_{\text{ik}} \times \text{EP}_k \mid}{\sum_{k=1}^{p} \text{EP}_k}$ | Olivoto et al. (2019) |
| AMMI-based stability parameter | ASTAB | $\text{ASTAB} = \sum_{n=1}^{N'} \lambda_n \gamma^2{}_{\text{in}}$ | Rao and Prabhakaran (2005) |
| Genotype stability index | GSI | $\text{GSI}_i = \text{RM}_i + \text{RA}_i$ | Farshadfar (2008) |
| Weighted average of absolute score | WAASB | $\text{WAASB} = \frac{\sum_{k=1}^{p} \mid \text{IPCA}_{ik} \times \text{EP}_k \mid}{\sum_{k=1}^{p} \text{EP}_k}$ | Olivoto et al. (2019) |
| Harmonic mean of genotypic value | HMGV | $\text{HMGV} = \frac{n}{\sum_{j=1}^{n} (\frac{1}{\text{GV}_{ij}})}$ | de Resende (2016) |
| Relative performance of genotypic value | RPGV | $\text{RPGV} = \frac{1}{n}[\sum_{j=1}^{n}(\frac{\text{GV}_{ij}}{\text{M}_j})]$ | de Resende (2016) |
| Harmonic mean of relative performance of genotypic value | HMRPGV | $\text{HMRPGV} = \frac{n}{\sum_{j=1}^{n} (\frac{1}{\text{RPGV}_{ij}})}$ | de Resende (2016) |
| Weighted average of weighted average of absolute score | WAASBY | $\text{WAASBY}_i = \frac{(\text{rG}_{i \times} \theta_y) + (\text{rW}_i \times \theta_s)}{\theta_y + \theta_s}$ | Olivoto et al. (2019) |

*Note*: ASV, AMMI stability value; $\text{SS}_{\text{IPCA1}}$, sum of squares for interaction principal component analysis axis I; $\text{SS}_{\text{IPCA2}}$, sum of squares for interaction principal component analysis axis II; MASI, modified AMMI stability index; $n$, number of principal components; PC$n$, score of $n$th principal component; $\theta_n$, percentage sum of squares explained by the $n$th principal component; WAAS, weighted average of absolute scores; IPCA, interaction principal component axis; $\text{IPCA}_{ik}$, score of the $i$th genotype in the $k$th IPCA; $\text{EP}_k$, variance of the $k$th IPCA; $p$, number of significant PCAs; ASTAB, AMMI-based stability parameter; $n$, number of significant IPCs; $\lambda_n$, singular value for $n$th IPC; $\gamma_{in,}$ eigenvector value for $i$th genotype; GSI, genotype stability index; $\text{RM}_i$, rank of trait mean for $i$th genotype; $\text{RA}_i$, rank of the AMMI stability value for the $i$th genotype; HMGV, harmonic means of genotypic value; $n$, number of environments; $\text{Gv}_{ij}$, genotypic value for the $i$th genotype in the $j$th environment; RPGV, relative performance of genotypic value; $\text{M}_{j,}$ mean of the environment $j$; HMRPGV, harmonic mean of relative performance of genotypic value; $n$, number of sites; $\text{RPGV}_{ij}$, RPGV genotypic value of the genotype $i$ in the environment $j$; WAASBY, weighted average of weighted average of absolute score; $\text{rG}_i$, rescaled value for grain yield; $\text{rW}_i$, rescaled value for WAASB; $\theta_Y$ and $\theta_S$, weight for response variable stability.

where $T_{\max}$ is the maximum temperature, $T_{\min}$ is the minimum temperature, and the $T_{\text{Base}}$ temperature for soybean is 10˚C.

## 3 | RESULTS

### 3.1 | Climate characteristics during crop growth

The mean air temperature at Müncheberg, Dahlem, and Dedelow from sowing to harvesting of soybeans over the 3 years was 16.1˚C, 17.6˚C, and 15.9˚C, respectively (Figure 1). The highest mean temperatures were recorded in 2019, with an average of 16.8˚C across all sites. June had the highest mean temperature of 21.2˚C across all locations, and it was higher than the 30-year average.

Mean precipitation during crop growth across the three locations was similar in 2020 and 2019 but differed significantly in 2021 (Figure 1). The mean precipitation from May to September for Dedelow, Müncheberg, and Dahlem over the 3 years was 298 mm, 249 mm, and 243 mm, respectively. Mean precipitation in Müncheberg and Dahlem was below the 30-year average. However, precipitation in 2021 in Dedelow was 28% higher than the 30-year average. Dedelow received the highest mean precipitation in July and August, during flowering and pod filling, with >55% occurring in 2021. Precipitation in July varied by year and location and was generally lower than the long-term average. August was dryer than the long-term average at all three locations in 2019 and 2020, except for Dedelow, which received 15 mm more precipitation in 2020.

The growing season lasted 139–153 days at Dedelow, 145–150 days at Müncheberg, and 130–145 days at Dahlem

**TABLE 4** Average grain yield and grain protein parameters at three sites in Northeast Germany (pooled data of 3 years).

| Location | Year | | | |
|---|---|---|---|---|
| **Grain yield (kg ha$^{-1}$)** | **2019** | **2020** | **2021** | **Average** |
| Müncheberg | 1863 | 1047 | 1670 | 1527b |
| Dahlem | 2095 | 1068 | 3286 | 2150a |
| Dedelow | – | 2396 | 2965 | 2503a |
| Average | 1979 | 1503 | 2640 | |
| **Crude protein (g kg$^{-1}$)** | | | | |
| Müncheberg | 374 | 401 | 415 | 396b |
| Dahlem | 412 | 428 | 430 | 423a |
| Dedelow | – | 331 | 394 | 383b |
| Average | 380 | 387 | 413 | |
| **Protein yield (kg ha$^{-1}$)** | | | | |
| Müncheberg | 701 | 420 | 691 | 604c |
| Dahlem | 865 | 457 | 1411 | 911b |
| Dedelow | – | 792 | 1178 | 960a |
| Average | 783 | 556 | 1183 | |

*Note*: Means followed by the same letter for each parameter are not significantly different at $p \leq 0.05$.

(Figure 2). The GDD ranged from 970 to 1066 at Dedelow, and the GDD ranged from 1005 to 1091 at Müncheberg. The average GDD at Dahlem was 1320 ± 24, ranging from 1293 to 1336. Dahlem accumulated 20% more GDD on average than Dedelow and Müncheberg. The average GDD was 1128 GDD across all environments. The average GDD in 2019 was higher than in 2020 and 2021.

## 3.2 | Grain and protein yields across environments

Grain yield varied significantly among the years and sites ($p < 0.01$). Mean soybean grain yield across years was 2060 kg ha$^{-1}$ and ranged from 1527 kg ha$^{-1}$ in Müncheberg to 2503 kg ha$^{-1}$ in Dedelow (Table 4). The highest mean grain yield of 2640 kg ha$^{-1}$ was observed in 2021, while the lowest of 1503 kg ha$^{-1}$ was observed in 2020. The mean grain yield in 2021 was 25% and 43% higher than what was observed in 2020 and 2019, respectively. Dahlem in the year 2021 produced the highest grain yield of 3286 kg ha$^{-1}$, followed by Dedelow in 2021, while the least grain yield of 1047 kg ha$^{-1}$ was achieved at Müncheberg in 2020.

The highest significant grain protein was found in soybean seeds harvested at Dahlem ($p < 0.01$), while the least was at Dedelow (Table 4). Consistently higher grain protein was observed at Dahlem in all 3 years. A higher mean grain protein content of 413 g kg$^{-1}$ was observed in 2021 and was significantly higher than in 2019 and 2020. However, Dedelow yielded 5% and 37% more protein than Dahlem and Müncheberg, respectively. The protein yield in 2021 was 1183 kg ha$^{-1}$ and was 33% and 53% higher compared to 2019 and 2020, respectively.

## 3.3 | AMMI analyses for grain and protein yields

Grain yield, crude protein, and protein yield of soybeans were significantly influenced by genotypes, environments, and their interactions (GEI) (Table 5). However, a large portion of the total variance in all studied parameters was explained by environment followed by GEI, while a small portion was attributed to the influence of genotypes. Environments contributed 82.8%, 67.6%, and 80.0% of total variation in grain yield, crude protein content, and protein yield in soybeans, respectively. The GEI accounted for 7.7%, 14.6%, and 11.1% variations in grain yield, crude protein content, and protein yield in soybeans, respectively. Genotypes contributed a small proportion of the variations in grain yield (1.4%) and protein yield (1.3%), and to a larger extent to the crude protein content (10.5%).

The partitioning of GEI revealed that the first four multiplicative terms (IPCA1, IPCA2, IPCA3, and IPCA4) of AMMI were significant for all studied parameters (Table 5). The cumulative contribution of IPCA1 and IPCA2 to the total GEI variance was 72.0% for grain yield, 80.4% for crude protein content, and 78.3% for protein yield. Environments and soybean genotypes with high stability are plotted close to the origin of the bi-plot, and vice versa (Figure 3).

The grain yield stability of the soybean cultivars varied, with cultivars Merlin and Sultana showing higher stability (close to origin) than the other genotypes. The AMMI1 biplot showed either positively or negatively interactive behaviors of six soybean cultivars across the eight environments (Figure 3). Across all locations and years, Siroca had the highest grain yield of 2194 kg ha$^{-1}$ followed by Comandor (2146 kg ha$^{-1}$),

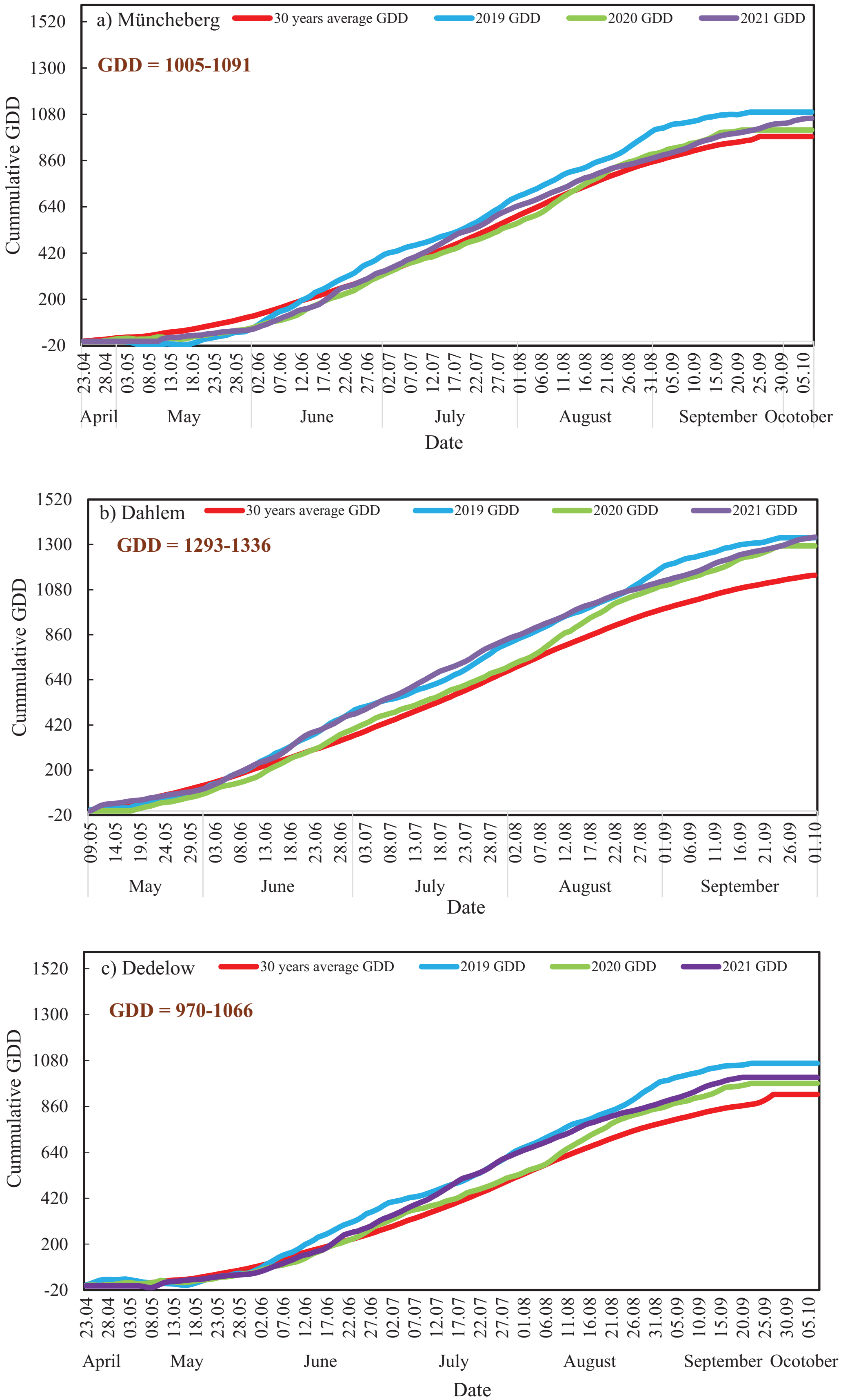


**FIGURE 2** (a) Cumulative GDD graphs of Müncheberg from sowing to harvesting from 2019 to 2021 compared to the 30 years average (1990–2020) in the area. GDD, growing degree days measured during the vegetation period. (b) Cumulative GDD graphs of Dahlem from sowing to

*(Continues)*

**FIGURE 2** (Continued)
harvesting from 2019 to 2021 compared to the 30 years average (1990–2020) in the area. GDD measured during the vegetation period. (c) Cumulative GDD graphs of Dedelow from sowing to harvesting from 2019 to 2021 compared to the 30 years average (1990–2020). GDD measured during the vegetation period.

**TABLE 5** Additive main effect and multiplicative interaction (AMMI) analysis of variance for grain yield and grain protein parameters.

| | | | Grain yield | | Crude protein | | Protein yield | |
|---|---|---|---|---|---|---|---|---|
| **Source** | ***df*** | ***p*-value** | **% SS explained** | **% G × E explained** | **% SS explained** | **% G × E explained** | **% SS explained** | **% G × E explained** |
| Genotypes (G) | 5 | | 1.4** | | 10.5** | | 1.3* | |
| Replication | 24 | | | | | | | |
| Environments | 7 | | 82.8** | | 67.6** | | 80.0** | |
| G × E | 35 | | 7.7** | | 14.6** | | 11.1** | |
| PC1 | 11 | | | 54.2** | | 59.2** | | 64.0** |
| PC2 | 9 | | | 17.8* | | 21.2** | | 14.3* |
| PC3 | 7 | | | 15.3* | | 10.1** | | 11.0* |
| PC4 | 5 | | | 9.6* | | 6.2* | | 7.6* |
| PC5 | 3 | | | 3.0ns | | 3.3ns | | 3.1ns |
| Residual | 120 | | 8.1 | | 7.3 | | 7.6 | |

Abbreviations: PC, principal component; SS, sum of squares.
*Significant at $p \leq 0.05$.
**Significant at $p \leq 0.05$; ns, non-significant at $p \leq 0.05$.

while Tofina (1895 kg ha$^{-1}$) had the lowest grain yield (Figure 3a; Table 6). Genotypes Tofina (417 g kg$^{-1}$) and Siroca (407 g kg$^{-1}$) showed the highest significant mean crude protein content across environments, while the lowest was found in Merlin (378 g kg$^{-1}$) (Table 5). Only Sultana and Tofina were stable genotypes for crude protein content across all environments (Figure 3b).

Cultivar Siroca yielded the highest protein (884 kg ha$^{-1}$) across all environments and years, yielding 13% higher protein than Sultana, which produced the least (Table 6). However, cultivars with lower average protein yields, that is, Merlin, Sultana, and Tofina, had more stable protein yields compared to Siroca and Comandor with higher protein yields (Figure 3c).

The AMMI2 biplot, constructed between the first two IPCAs, details the interaction of soybean genotypes with the environments (Figure 4). Genotypes and environments near the biplot's origin have the least influence on GEI, and vice versa. Hence, Merlin, like the AMMI1 biplot, showed the highest stability and least influence on GEI for grain yield. On the other hand, in terms of grain protein content, Siroca, Sultana, and Comandor contributed more to the GEI (Figure 4b). Genotypes Merlin and Tofina showed broad stability for grain protein content in all environments. In contrast, there was no stable genotype for protein yield (Figure 4c). In 2021, Müncheberg and Dedelow exhibited stronger interactive forces for grain yield, whereas both environments in Dedelow consistently elicited strong interactions for grain protein content.

## 3.4 | BLUP analyses for grain yield

There was a large distribution of soybean genotypes based on mean performance (grain yield and crude protein content) and stability across environments (Figure 5). In the first quadrant, low-yielding and highly unstable genotypes along with highly discriminating environments are included. Genotypes Sultana and Tofina with high WAASB values and lower mean yields than the grand mean are plotted. The second quadrant comprised unstable but high-yielding genotypes. The genotypes plotted in the second genotype are Siroca, Shouna, and Comandor. Environments in the second quadrant are discriminative among the genotypes and comprised Dahlem and Dedelow in 2019 and 2021, respectively.

The third quadrant included all three trial years in Müncheberg and Dahlem in 2020. These environments are low-yielding with minimum discrimination, but they are more stable. No genotype was included in the third quadrant. The fourth quadrant comprised only genotype Merlin, characterized by wide adaptability, high yield, and low WAASB value. Genotypes and environments were plotted in the same quadrants as in Figure 5 when grain and protein yields were considered for mean performance determination (Figure S1).

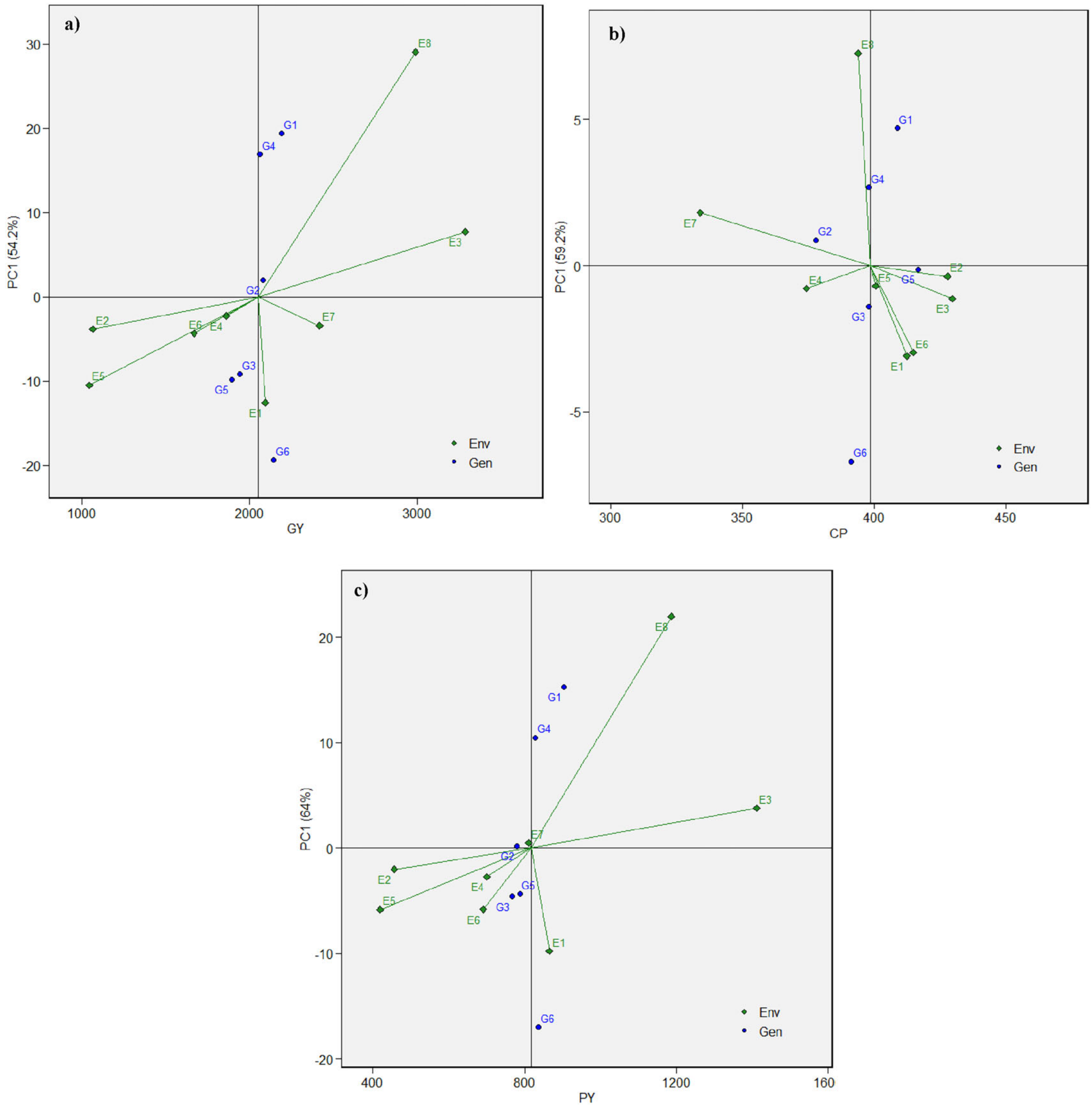


**FIGURE 3** Additive main effect and multiplicative interaction one biplot for (a) grain yield, (b) and crude protein content versus PC1 of six soybean genotypes evaluated in eight environments. Env, environment; Gen, genotype; GY, grain yield; CP, crude protein; PY, protein yield. G1, Siroca; G2, Merlin; G3, Sultana; G4, Shouna; G5, Tofina; G6, Comandor. E1, Dahlem 2019; E2, Dahlem 2020; E3, Dahlem 2021; E4, Müncheberg; E5, Müncheberg; E6, Müncheberg; E7, Dedelow; E8, Dedelow. (c). Additive main effect and multiplicative interaction one biplot for (c) protein yield versus PC1 of six soybean genotypes evaluated in eight environments. Env, environment; Gen, genotype; GY, grain yield; CP, crude protein; PY, protein yield. G1, Siroca; G2, Merlin; G3, Sultana; G4, Shouna; G5, Tofina; G6, Comandor. E1, Dahlem 2019; E2, Dahlem 2020; E3, Dahlem 2021; E4, Müncheberg; E5, Müncheberg; E6, Müncheberg; E7, Dedelow; E8, Dedelow.

## 3.5 | Selection of superior genotypes based on mean performance and stability

The performance and stability indexes revealed large variations in grain yield, grain protein, and protein yield among the six genotypes. All AMMI stability indexes consistently revealed Merlin to be the most stable genotype for grain yield, while Comandor was the least stable (Table 6). This is consistent with the BLUP-based WAASB index (Table 7). Similarly, based on GSI and WAASBY, Merlin was the most desirable genotype for stable and high-grain yield selection. While the AMMI model selected Comandor as the least desired genotype for grain yield, the BLUP model identified Tofina as the least.

Tofina with lower ASV, MASI, ASTAB, and GSI was consistently the most stable and superior genotype for grain protein content. In contrast, Comandor was the least desirable genotype for grain protein content. This is consistent with the BLUP model's lower HMGV, WAASB, and WAASBY indices for Comandor. Merlin and Tofina exhibited lower GSI values and were identified as superior genotypes for protein yield. This is contrasted by the BLUP model, which selected

**TABLE 6** Means and additive main effect and multiplicative interaction (AMMI)-based stability values for grain yield and grain protein parameters.

| Trait | Cultivar | Mean | ASV | MASI | WAAS | ASTAB | GSI |
|---|---|---|---|---|---|---|---|
| Grain yield, (kg ha$^{-1}$) | | | | | | | |
| | Siroca | 2194 | 59.6 | 10.6 | 13.6 | 9.6 | 18 |
| | Merlin | 2084 | 9.5 | 1.7 | 5.3 | 4.5 | 7 |
| | Sultana | 1946 | 33.9 | 6.0 | 9.5 | 9.0 | 19 |
| | Shouna | 2064 | 52.3 | 9.3 | 12.6 | 9.5 | 20 |
| | Tofina | 1895 | 30.2 | 5.4 | 9.5 | 10.0 | 18 |
| | Comandor | 2146 | 60.4 | 10.7 | 15.5 | 11.4 | 23 |
| Crude protein, (g kg$^{-1}$) | | | | | | | |
| | Siroca | 407** | 16.9 | 2.9 | 53.2 | 3.1 | 21 |
| | Merlin | 378 | 3.3 | 0.6 | 47.2 | 0.9 | 16 |
| | Sultana | 398 | 5.7 | 1.3 | 68.2 | 1.2 | 16 |
| | Shouna | 398 | 9.5 | 1.6 | 55.1 | 2.2 | 17 |
| | Tofina | 417** | 0.8 | 0.3 | 100 | 0.7 | 6 |
| | Comandor | 391 | 26.1 | 4.0 | 17.1 | 4.3 | 29 |
| Protein yield, (kg N ha$^{-1}$) | | | | | | | |
| | Siroca | 884 | 57.3 | 9.9 | 61.7 | 10.2 | 17 |
| | Merlin | 781 | 9.8 | 1.4 | 55.4 | 3.0 | 12 |
| | Sultana | 768 | 19.4 | 3.2 | 38.1 | 4.8 | 19 |
| | Shouna | 829 | 45.9 | 6.7 | 44.6 | 7.3 | 19 |
| | Tofina | 788 | 19.2 | 3.0 | 46.0 | 4.8 | 12 |
| | Comandor | 837 | 69.7 | 10.9 | 29.9 | 10.8 | 26 |

Abbreviations: ASTAB, AMMI-based stability parameter; ASV, AMMI stability value; GSI, genotype stability index; MASI, modified AMMI stability index; WAAS, weighted average of absolute scores.
**Significant at $p \leq 0.05$ probability level.

Siroca with a higher WAASBY index to be superior for protein yield.

## 4 | DISCUSSION

### 4.1 | Climatic influence on soybean yield

The observed average grain yield of 2060 kg ha$^{-1}$ in the three trial areas is fair for the non-traditional production environment of Northeast Germany, which is characterized by low soil quality and low precipitation (Figure 1). Drought continues to hinder soybean production in Central Europe, and its influence is projected to increase in the future (Nendel et al., 2023). It often coincides with seedling emergence and flowering, resulting in crop failure and severe yield losses. In this experiment, although the total amount of rainfall differed marginally over the growing seasons, there was substantial variation in its distribution across the studied locations. There was low precipitation at all locations in all trial years in spring (April–May), which was before and during the early development period of soybean, while an irregular pattern was seen from June till harvesting. This may have resulted in varying drought stress events during crop growth, emphasizing the importance of breeding drought-tolerant cultivars for Central European environments. Fairly high and regular rainfall at Dedelow from June to August in the year 2021 was enough to avert the impacts of drought, which likely influenced the observed high grain yield that year. Besides the influence of regular precipitation during the critical stage of crop growth, early sowing (late April to early May) at Dedelow in all 3 years may have positively influenced grain yield. In Poland, Borowska and Prusiński (2021) found that soybeans seeded between late April and early May yielded more seeds than those sown in mid-May.

Temperature summation expressed as GDD is important in soybean production and has been used to predict the soybean crop growth stages and identify optimal production locations (Akyuz et al., 2017; Kühling et al., 2018). GDD varied among the three sites due to climatic variables and showing dates. Except for Dahlem, GDD was within the range of values reported by Karges et al. (2022) for Northeast Germany. High maximum temperatures in all 3 years at Dahlem corresponded with higher GDD and shorter

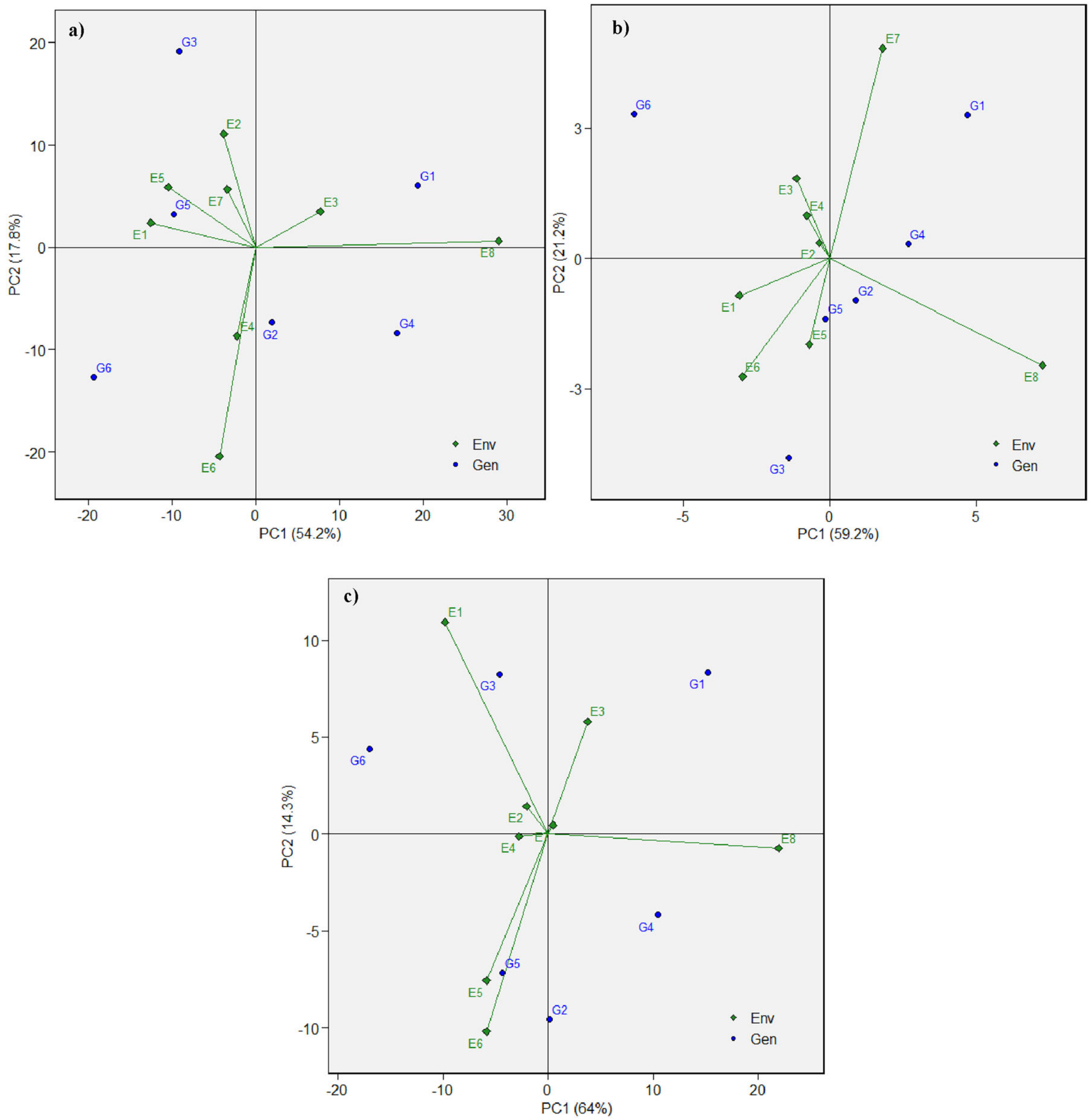


**FIGURE 4** Additive main effect and multiplicative interaction two biplot (PC1 vs. PC2) for (a) grain yield and (b) crude protein of six soybean genotypes evaluated in eight environments. Env, environment; Gen, genotype; GY, grain yield; CP, crude protein; PY, protein yield. G1, Siroca; G2, Merlin; G3, Sultana; G4, Shouna; G5, Tofina; G6, Comandor. E1, Dahlem 2019; E2, Dahlem 2020; E3, Dahlem 2021; E4, Müncheberg; E5, Müncheberg; E6, Müncheberg; E7, Dedelow; E8, Dedelow. (c). Additive main effect and multiplicative interaction two biplot (PC1 vs. PC2) for protein yield of six soybean genotypes evaluated in eight environments. Env, environment; Gen, genotype; GY, grain yield; CP, crude protein; PY, protein yield. G1, Siroca; G2, Merlin; G3, Sultana; G4, Shouna; G5, Tofina; G6, Comandor. E1, Dahlem 2019; E2, Dahlem 2020; E3, Dahlem 2021; E4, Müncheberg; E5, Müncheberg; E6, Müncheberg; E7, Dedelow; E8, Dedelow.

vegetation period (10 days less) than Müncheberg and Dedelow. High temperature is known to shorten the seed-filling time and promote early ripening (Chimenti et al., 2001), and that has implications for grain yield and grain quality composition (Hu & Wiatrak, 2012; Kumagai & Sameshima, 2014). In this experiment, high GDD corresponded with high grain protein content at Dahlem. Environments with higher grain protein content often tend to have lower grain yields, but this was not the case in Dahlem with significantly higher protein content and higher grain yield compared to Müncheberg (Table 4). While a meta-analysis by Rotundo and Westgate (2009) revealed a negative influence of increased temperature on grain protein content, Makuch et al. (2023) observed no link between the two variables in subtropical conditions in Brazil. Thus, further studies with larger datasets from multiple places and years are required to disentangle the impacts of individual climatic variables on soybean protein content and yield.

**TABLE 7** Means and best linear unbiased prediction (BLUP)-based stability values for grain yield and grain protein parameters.

| Trait | Cultivar | Mean | HMGV | HMRPGV | RPGV | WAASB | WAASBY |
|---|---|---|---|---|---|---|---|
| Grain yield, (kg ha$^{-1}$) | | | | | | | |
| | Siroca | 2194 | 68.8 | 1.02 | 1.03 | 10.2 | 71.1 |
| | Merlin | 2084 | 85.8 | 1.01 | 1.01 | 4.4 | 76.0 |
| | Sultana | 1946 | 38.4 | 0.96 | 0.97 | 8.8 | 33.1 |
| | Shouna | 2064 | 45.8 | 0.98 | 0.99 | 9.6 | 44.2 |
| | Tofina | 1895 | 29.4 | 0.95 | 0.96 | 9.7 | 23.2 |
| | Comandor | 2146 | 47.6 | 1.04 | 1.04 | 11.3 | 54.5 |
| Crude protein, (g kg$^{-1}$) | | | | | | | |
| | Siroca | 407** | 53.2 | 1.02 | 1.03 | 3.2 | 61.8 |
| | Merlin | 378 | 47.2 | 0.95 | 0.96 | 1.0 | 34.3 |
| | Sultana | 398 | 68.2 | 1.0 | 0.99 | 1.8 | 55.9 |
| | Shouna | 398 | 55.1 | 1.0 | 0.99 | 1.9 | 58.4 |
| | Tofina | 417** | 100 | 1.04 | 1.04 | 0.7 | 100.0 |
| | Comandor | 391 | 17.1 | 0.98 | 0.98 | 4.1 | 22.2 |
| Protein yield, (kg N ha$^{-1}$) | | | | | | | |
| | Siroca | 884 | 61.7 | 1.04 | 1.05 | 10.5 | 68.9 |
| | Merlin | 781 | 55.4 | 0.96 | 0.97 | 3.2 | 41.0 |
| | Sultana | 768 | 38.1 | 0.95 | 0.96 | 4.9 | 27.2 |
| | Shouna | 829 | 44.6 | 0.97 | 0.99 | 7.3 | 40.2 |
| | Tofina | 788 | 46.0 | 0.98 | 0.99 | 4.6 | 37.8 |
| | Comandor | 837 | 29.9 | 1.01 | 1.03 | 10.5 | 32.9 |

Abbreviations: HMGV, harmonic means of genotypic values; HMRPGV, harmonic mean of relative performance of genotypic values; RPGV, relative performance of genotypic values; WAASB, weighted average of absolute scores; WAASBY, weighted average of the stability and mean performance.

**Significant at $p \leq 0.05$ probability level.

## 4.2 | Genotype and environment interaction on studied traits

Combined ANOVA revealed that all components of variation, that is, environment, genotype, and GEI, were significant for all the parameters studied (Table 5). The greater magnitude of environment and GEI than genotype reflected not only the effect of environment on soybean production but also the differential performance of soybean genotypes under diverse agro-environmental conditions in Northeast Germany. The contribution of the GEI to total variation in soybean grain yield may vary greatly from place to place. While such studies are limited in Europe, there are examples from Africa and Asia, that is, 6.1% at four sites in eastern, northern, central, and western Uganda (Tukamuhabwa et al., 2012), 40.7% at different altitudes of the north-western Himalayan hills in India (Bhartiya et al., 2017), 47.4% at six environments in southern Africa (Zambia, Zimbabwe, Malawi, and Mozambique) (Mwiinga et al., 2020), and 59.6% in northwestern Ethiopia (Atnaf et al., 2013). The current study found low GEI, which can be attributed to commonalities in critical stress factors among the three studied sites, that is, Dahlem, Müncheberg, and Dedelow (Ceccarelli, 1989). However, despite being marked as less productive, the Müncheberg site consistently showed low discrimination on genotypes, making it a suitable site for stable and repeatable soybean genotype evaluation (Ito et al., 2016; Yan & Kang, 2002). Dedelow and Dahlem showed inconsistent discrimination on genotypes.

The fact that environment and GEI were the largest contributors to overall variance implies the need for assessment of genotypes in diverse environments (Khan et al., 2021), even if they are close to each other (<120 km distance) like in the present study. This will enable the selection of genotypes suitable for specific conditions for optimal yield performance and reduced yield variability (Yan & Tinker, 2006). Genotypes' contribution to overall variance, particularly in grain and protein yield, was low, indicating the narrow genetic background of the studied genotypes. This is surprising as cultivars were selected based on certain traits, that is, maturity period, food or feed grade, growth habit, yield potential, etc. This observation could be utilized in breeding programs for the identification of elite soybean cultivars. The contribution of genotypes was eight times higher for grain protein content than grain yield and protein yield. Similarly, Sudarić et al. (2006) found that genotypes had a greater influence on grain protein content compared to oil content and grain yield.

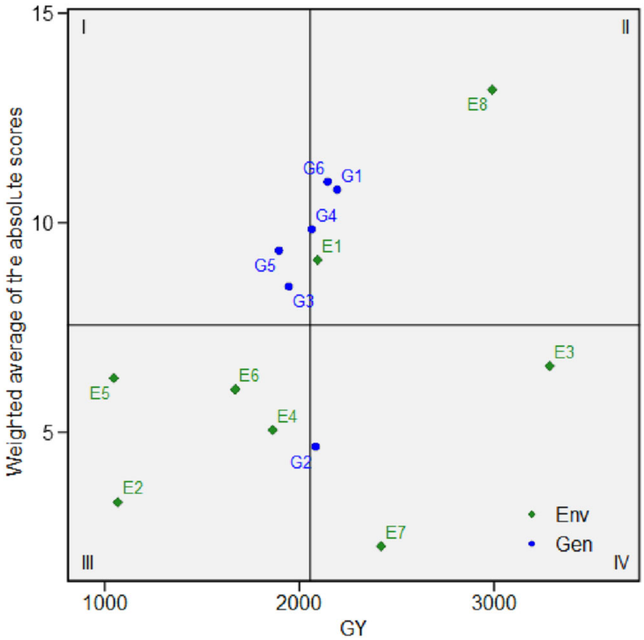


**FIGURE 5** Best linear unbiased prediction biplot of (a) grain yield versus weighted average of the absolute scores of six soybean genotypes evaluated in eight environments. (Higher weight of 60 for grain yield and lower weight of 40 for crude protein). Env, environment; Gen, genotype; GY, grain yield. G1, Siroca; G2, Merlin; G3, Sultana; G4, Shouna; G5, Tofina; G6, Comandor. E1, Dahlem 2019; E2, Dahlem 2020; E3, Dahlem 2021; E4, Müncheberg 2019; E5, Müncheberg 2020; E6, Müncheberg 2021; E7, Dedelow 2020; E8, Dedelow 2021. I, first quadrant (upper left); II, second quadrant (upper right); III, third quadrant (lower left); IV, fourth quadrant (lower right).

The partitioning of GEI using the AMMI revealed that four IPCAs were significant, with the first two contributing 72.0%, 80.4%, and 78.3% of total GEI in grain yield, crude protein, and protein yield, respectively. This justifies the estimation of the phenotypic stability of genotypes over environments (Farshadfar & Sutka, 2006; Gauch, 2013).

### 4.3 | Superior genotypes based on mean performance and stability

Yield performance and stability in grain legumes, particularly in Europe, are essential considerations because they are among the major obstacles inhibiting farmer adoption (Döring, 2015; Magrini et al., 2016). In the current research, after revealing the existence of significant GEI for all studied parameters, multiple stability indices were employed to identify superior genotypes in terms of performance and stability in different environments. While there were variations in the stability of the genotypes, there were only slight variations in the grain yield performances.

Different AMMI and BLUP stability values have previously been used to rank different forage and grain legume genotypes (Ajay et al., 2020; Anuradha et al., 2022; Hakl et al., 2019; Nataraj et al., 2021). The indices utilized in this study, regardless of whether being BLUP or AMMI-based, picked the same winners in most cases in the simultaneous evaluation of stable and high-yielding genotypes. This implies that both models were equally effective at selecting desirable genotypes. For example, in terms of grain yield, cultivar Merlin was highly stable according to the BLUP and AMMI models and showed high superiority based on the GSI and WAASBY indices. This finding agrees with Karges et al. (2022), who observed high grain stability in Merlin in rainfed conditions at Müncheberg. Cultivar Merlin is the oldest of the cultivars tested in the present study, and its high stability may be because of its hardiness, early seedling vigor (Fordoński et al., 2023; Rymuza & Radzka, 2023), slender stems with an average biomass yield, and grain yield potential, which favor its cultivation in drought-prone Northeast Germany. Comandor, although high-yielding across environments, showed less superiority in all measured parameters because of its low stability. Cultivar Tofina had the greatest crude protein content with a high superiority and stability measure across different environments. Cultivar Tofina was released and is well-known in Germany for making tofu.

## 5 | CONCLUSION

We showed that the prevailing climatic conditions in Central Europe support rainfed soybean cultivation. However, soybean yield potential is jeopardized by variable rainfall patterns and spring droughts. Based on our ANOVA, we demonstrated a large environmental effect on the variances in soybean grain yield, grain protein content, and protein yield. The genotype effect on the overall variance was small. While grain yield differences among genotypes were minimal, their performance varied with the environment, and the top-yielding genotypes were not stable across environments.

The AMMI and BLUP stability models identified Merlin as the most stable genotype. In contrast, high-yielding Comandor showed low stability. The site Müncheberg had the most stable soybean production at a lower grain yield level, while the other two sites were more productive despite having uneven genotype discrimination abilities. We conclude that breeding is important for securing high-yielding soybean cultivars adapted to northern conditions. Stability of grain and protein yield, particularly in food-grade cultivars, should be considered for the profitability of soybean production in non-traditional areas.

## AUTHOR CONTRIBUTIONS

**Richard Ansong Omari**: Data curation; formal analysis; investigation; methodology; writing—original draft; writing—review and editing. **Mosab Halwani**: Formal

analysis; investigation; methodology; writing—review and editing. **Moritz Reckling**: Conceptualization; funding acquisition; methodology; writing—review and editing. **Ma Hua**: Conceptualization; methodology. **Sonoko D. Bellingrath-Kimura**: Conceptualization; funding acquisition; project administration; writing—review and editing.

## ACKNOWLEDGMENTS

We acknowledge financial support for this work from the SusCrop-ERA-NET through the project "LegumeGap" (Grant No. 031B0807B) and the BMBF via Bioökonomie International through the "FiSBea" project (Grant No. 031B1212). We are also grateful to the staff of the Albrecht Daniel Thaer Institute of Agricultural and Horticultural Sciences, Humboldt Universität zu Berlin, Dahlem, and the ZALF Experimental Stations in Müncheberg and Dedelow for their support during the fieldwork. We are thankful to Gunhild Rosner, Kathleen Karges, and Michael Baumecker for making all required data sets available to us.

Open access funding enabled and organized by Projekt DEAL.

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data will be available on request.

## ORCID

*Richard Ansong Omari* https://orcid.org/0000-0002-4201-6233

## REFERENCES

Ajay, B. C., Bera, S. K., Singh, A. L., Kumar, N., Gangadhar, K., & Kona, P. (2020). Evaluation of genotype × environment interaction and yield stability analysis in peanut under phosphorus stress condition using stability parameters of AMMI model. *Agricultural Research*, *9*(4), 477–486. https://doi.org/10.1007/s40003-020-00458-3

Akyuz, F. A., Kandel, H., & Morlock, D. (2017). Developing a growing degree day model for North Dakota and Northern Minnesota soybean. *Agricultural and Forest Meteorology*, *239*, 134–140. https://doi.org/10.1016/j.agrformet.2017.02.027

Albaladejo Román, A. (2023). *EU protein strategy*. European Parliamentary Research Service.

Anuradha, N., Patro, T. S. S. K., Singamsetti, A., Sandhya Rani, Y., Triveni, U., Nirmala Kumari, A., Govanakoppa, N., Lakshmi Pathy, T., & Tonapi, V. A. (2022). Comparative study of AMMI- and BLUP-based simultaneous selection for grain yield and stability of finger millet [*Eleusine coracana* (L.) Gaertn.] genotypes. *Frontiers in Plant Science*, *12*, Article 786839. https://doi.org/10.3389/fpls.2021.786839

Atnaf, M., Kidane, S., Abadi, S., & Fisha, Z. (2013). GGE biplots to analyze soybean multi-environment yield trial data in north Western Ethiopia. *Journal of Plant Breeding and Crop Science*, *5*(12), 245–254. https://doi.org/10.5897/jpbcs13.0403

BAES. (2025). *Mittel- und großsamige Leguminosen*. Bundesamt für Ernährungssicherheit. https://bsl.baes.gv.at/kulturen/mittel-und-grosssamige-leguminosen/#c7123

Bhartiya, A., Aditya, J. P., Kumari, V., Kishore, N., Purwar, J. P., Agrawal, A., & Kant, L. (2017). GGE biplot & AMMI analysis of yield stability in multi-environment trial of soybean [*Glycine Max* (L.) Merrill] genotypes under rainfed condition of north western Himalayan hills. *The Journal of Animal & Plant Sciences*, *27*(1), 227–238.

Bocianowski, J., Niemann, J., & Nowosad, K. (2019). Genotype-by-environment interaction for seed quality traits in interspecific cross-derived *Brassica* lines using additive main effects and multiplicative interaction model. *Euphytica*, *215*, Article 7. https://doi.org/10.1007/s10681-018-2328-7

Bocianowski, J., Warzecha, T., Nowosad, K., & Bathelt, R. (2019). Genotype by environment interaction using AMMI model and estimation of additive and epistasis gene effects for 1000-kernel weight in spring barley (*Hordeum vulgare* L.). *Journal of Applied Genetics*, *60*(2), 127–135. https://doi.org/10.1007/s13353-019-00490-2

Boerema, A., Peeters, A., Swolfs, S., Vandevenne, F., Jacobs, S., Staes, J., & Meire, P. (2016). Soybean trade: Balancing environmental and socio-economic impacts of an intercontinental market. *PLoS One*, *11*(5), 1–13. https://doi.org/10.1371/journal.pone.0155222

Borowska, M., & Prusiński, J. (2021). Effect of soybean cultivars sowing dates on seed yield and its correlation with yield parameters. *Plant, Soil and Environment*, *67*(6), 360–366. https://doi.org/10.17221/73/2021-pse

Bundessortenamt. (2021). *Beschreibende Sortenliste: Getreide, Mais Öl- und Faserpflanzen Leguminosen Rüben Zwischenfrüchte*. Bundessortenamt. https://www.bundessortenamt.de/bsa/media/Files/BSL/bsl_getreide_2021.pdf

Ceccarelli, S. (1989). Wide adaptation: How wide? *Euphytica*, *40*, 197–205. https://doi.org/10.1007/BF00024512

Chenu, K., Cooper, M., Hammer, G. L., Mathews, K. L., Dreccer, M. F., & Chapman, S. C. (2011). Environment characterization as an aid to wheat improvement: Interpreting genotype-environment interactions by modelling water-deficit patterns in North-Eastern Australia. *Journal of Experimental Botany*, *62*(6), 1743–1755. https://doi.org/10.1093/jxb/erq459

Chimenti, C. A., Hall, A. J., & López, S. M. (2001). Embryo-growth rate and duration in sunflower as affected by temperature. *Field Crops Research*, *69*, 81–88.

de Resende, M. D. V. (2016). Software Selegen-REML/BLUP: A useful tool for plant breeding. *Crop Breeding and Applied Biotechnology*, *16*(4), 330–339. https://doi.org/10.1590/1984-70332016v16n4a49

Döring, T. (2015). Grain legume cropping systems in temperate climates. In A. De Ron (Ed.), *Grain legumes* (pp. 401–434). Springer. https://doi.org/10.1007/978-1-4939-2797-5_13

EUROStat. (2021). *EU Schlüsselindikatoren*. European Union. https://ec.europa.eu/eurostat/de/

Farshadfar, E. (2008). Incorporation of AMMI stability value and grain yield in a single non-parametric index (GSI) in bread wheat. *Pakistan Journal of Biological Science*, *11*(14), 1791–1796. https://doi.org/10.3923/pjbs.2008.1791.1796

Farshadfar, E., & Sutka, J. (2006). Biplot analysis of genotype-environment interaction in durum wheat using the AMMI model. *Acta Agronomica Hungarica*, *54*(4), 459–467. https://doi.org/10.1556/AAgr.54.2006.4.8

Fordoński, G., Okorski, A., Olszewski, J., Dąbrowska, J., & Pszczółkowska, A. (2023). The effect of sowing date on the growth and yield of soybeans cultivated in north-eastern Poland. *Agriculture*, *13*(12), 1–18. https://doi.org/10.3390/agriculture13122199

Gauch, H. G. (2013). A simple protocol for AMMI analysis of yield trials. *Crop Science*, *53*(5), 1860–1869. https://doi.org/10.2135/cropsci2013.04.0241

Gudmundsson, L., & Seneviratne, S. I. (2016). Anthropogenic climate change affects meteorological drought risk in Europe. *Environmental Research Letters*, *11*, 044005. https://doi.org/10.1088/1748-9326/11/4/044005

Hakl, J., Mofidian, S. M. A., Kozová, Z., Fuksa, P., & Jaromír, Š. (2019). Estimation of lucerne yield stability for enabling effective cultivar selection under rainfed conditions. *Grass and Forage Science*, *74*(4), 687–695. https://doi.org/10.1111/gfs.12456

Halwani, M., Reckling, M., Schuler, J., Bloch, R., & Bachinger, J. (2019). Soybean in no-till cover-crop systems. *Agronomy*, *9*(12), 883. https://doi.org/10.3390/agronomy9120883

Hu, M., & Wiatrak, P. (2012). Effect of planting date on soybean growth, yield, and grain quality: Review. *Agronomy Journal*, *104*(3), 785–790. https://doi.org/10.2134/agronj2011.0382

Ito, D., Afshar, R. K., Chen, C., Miller, P., Kephart, K., McVay, K., Lamb, P., Miller, J., Bohannon, B., & Knox, M. (2016). Multienvironmental evaluation of dry pea and lentil cultivars in Montana using the AMMI model. *Crop Science*, *56*(2), 520–529. https://doi.org/10.2135/cropsci2015.01.0032

Karges, K., Bellingrath-Kimura, S. D., Watson, C. A., Stoddard, F. L., Halwani, M., & Reckling, M. (2022). Agro-economic prospects for expanding soybean production beyond its current northerly limit in Europe. *European Journal of Agronomy*, *133*, 126415. https://doi.org/10.1016/j.eja.2021.126415

Karlsson, J. O., Parodi, A., van Zanten, H. H. E., Hansson, P. A., & Röös, E. (2021). Halting European Union soybean feed imports favours ruminants over pigs and poultry. *Nature Food*, *2*(1), 38–46. https://doi.org/10.1038/s43016-020-00203-7

Khan, M. M. H., Rafii, M. Y., Ramlee, S. I., Jusoh, M., & Al Mamun, M. (2021). AMMI and GGE biplot analysis for yield performance and stability assessment of selected Bambara groundnut (*Vigna subterranea* L. Verdc.) genotypes under the multi-environmental trails (METs). *Scientific Reports*, *11*, Article 22791. https://doi.org/10.1038/s41598-021-01411-2

Köhler, I. H., Huber, S. C., Bernacchi, C. J., & Baxter, I. R. (2019). Increased temperatures may safeguard the nutritional quality of crops under future elevated $CO_2$ concentrations. *The Plant Journal*, *97*(5), 872–886. https://doi.org/10.1111/tpj.14166

Korres, N. E., Norsworthy, J. K., Tehranchian, P., Gitsopoulos, T. K., Loka, D. A., Oosterhuis, D. M., Gealy, D. R., Moss, S. R., Burgos, N. R., Miller, M. R., & Palhano, M. (2016). Cultivars to face climate change effects on crops and weeds: A review. *Agronomy for Sustainable Development*, *36*, Article 12. https://doi.org/10.1007/s13593-016-0350-5

Krul, E. S. (2019). Calculation of nitrogen-to-protein conversion factors: A review with a focus on soy protein. *Journal of the American Oil Chemists' Society*, *96*(4), 339–364. https://doi.org/10.1002/aocs.12196

Kühling, I., Hüsing, B., Bome, N., & Trautz, D. (2018). Soybeans in high latitudes: Effects of *Bradyrhizobium* inoculation in Northwest Germany and southern West Siberia. *Organic Agriculture*, *8*(2), 159–171. https://doi.org/10.1007/s13165-017-0181-y

Kumagai, E., & Sameshima, R. (2014). Genotypic differences in soybean yield responses to increasing temperature in a cool climate are related to maturity group. *Agricultural and Forest Meteorology*, *198–199*, 265–272. https://doi.org/10.1016/j.agrformet.2014.08.016

Li, Y., Ye, W., Wang, M., & Yan, X. (2009). Climate change and drought: A risk assessment of crop-yield impacts. *Climate Research*, *39*, 31–46. https://doi.org/10.3354/cr00797

Magrini, M.-B., Anton, M., Cholez, C., Corre-Hellou, G., Duc, G., Jeuffroy, M.-H., Meynard, J.-M., Pelzer, E., Voisin, A.-S., & Walrand, S. (2016). Why are grain-legumes rarely present in cropping systems despite their environmental and nutritional benefits? Analyzing lock-in in the French agrifood system. *Ecological Economics*, *126*, 152–162. https://doi.org/10.1016/j.ecolecon.2016.03.024

Makuch, E. I., Umburanas, R. C., Yokoyama, A. H., Spader, V., & Kawakami, J. (2023). Soybean yield of grain, oil, and protein as a function of cultivar, field environments and water restriction in controlled environment in Southern Brazil. *International Journal of Plant Production*, *17*(3), 593–605. https://doi.org/10.1007/s42106-023-00257-0

McMaster, G. S., & Wilhelm, W. W. (1997). Growing degree-days: One equation, two interpretations. *Agricultural and Forest Meteorology*, *87*, 291–300. https://doi.org/10.1016/S0168-1923(97)00027-0

Mwiinga, B., Sibiya, J., Kondwakwenda, A., Musvosvi, C., & Chigeza, G. (2020). Genotype x environment interaction analysis of soybean (*Glycine max* (L.) Merrill) grain yield across production environments in Southern Africa. *Field Crops Research*, *256*, 107922. https://doi.org/10.1016/j.fcr.2020.107922

Nataraj, V., Bhartiya, A., Singh, C. P., Devi, H. N., Deshmukh, M. P., Verghese, P., Singh, K., Mehtre, S. P., Kumari, V., Maranna, S., Kumawat, G., Ratnaparkhe, M. B., Satpute, G. K., Rajesh, V., Chandra, S., Ramteke, R., Khandekar, N., & Gupta, S. (2021). WAASB-based stability analysis and simultaneous selection for grain yield and early maturity in soybean. *Agronomy Journal*, *113*(4), 3089–3099. https://doi.org/10.1002/agj2.20750

Nendel, C., Reckling, M., Debaeke, P., Schulz, S., Berg-Mohnicke, M., Constantin, J., Fronzek, S., Hoffmann, M., Jakšic, S., Kersebaum, K. C., Klimek-Kopyra, A., Raynal, H., Schoving, C., Stella, T., & Battisti, R. (2023). Future area expansion outweighs increasing drought risk for soybean in Europe. *Global Change Biology*, *29*(5), 1340–1358. https://doi.org/10.1111/gcb.16562

Olivoto, T., & Lúcio, A. D. C. (2020). metan: An R package for multi-environment trial analysis. *Methods in Ecology and Evolution*, *11*, 783–789. https://doi.org/10.1111/2041-210x.13384

Olivoto, T., Lúcio, A. D. C., da Silva, J. A. G., Marchioro, V. S., de Souza, V. Q., & Jost, E. (2019). Mean performance and stability in multi-environment trials I: Combining features of AMMI and BLUP techniques. *Agronomy Journal*, *111*(6), 2949–2960. https://doi.org/10.2134/agronj2019.03.0220

Omari, R. A., Yuan, K., Anh, K. T., Reckling, M., Halwani, M., Egamberdieva, D., Ohkama-Ohtsu, N., & Bellingrath-Kimura, S. D. (2022). Enhanced soybean productivity by inoculation with indigenous *Bradyrhizobium* Strains in agroecological conditions of northeast Germany. *Front Plant in Science*, *12*, Article 707080. https://doi.org/10.3389/fpls.2021.707080

Picasso, V. D., Casler, M. D., & Undersander, D. (2019). Resilience, stability, and productivity of alfalfa cultivars in rainfed regions of north America. *Crop Science*, *59*(2), 800–810. https://doi.org/10.2135/cropsci2018.06.0372

Purchase, J. L., Hatting, H., & van Deventer, C. S. (2000). Genotype × environment interaction of winter wheat (*Triticum aestivum* L.) in South Africa: II. Stability analysis of yield performance. *South African Journal of Plant and Soil*, *17*(3), 101–107. https://doi.org/10.1080/02571862.2000.10634878

Rao, A. R., & Prabhakaran, V. T. (2005). Use of AMMI in simultaneous selection of genotypes for yield and stability. *Journal of the Indian Society of Agricultural Statistics*, *59*(1), 76–82.

Reckling, M., Ahrends, H., Chen, T.-W., Eugster, W., Hadasch, S., Knapp, S., Laidig, F., Linstädter, A., Macholdt, J., Piepho, H.-P., Schiffers, K., & Döring, T. F. (2021). Methods of yield stability analysis in long-term field experiments. A review. *Agronomy for Sustainable Development*, *41*(27), 1–28. https://doi.org/10.1007/s13593-021-00681-4

Reckling, M., Bergkvist, G., Watson, C. A., Stoddard, F. L., & Bachinger, J. (2020). Re-designing organic grain legume cropping systems using systems agronomy. *European Journal of Agronomy*, *112*, 125951. https://doi.org/10.1016/j.eja.2019.125951

Reckling, M., Döring, T. F., Bergkvist, G., Stoddard, F. L., Watson, C. A., Seddig, S., Chmielewski, F. M., & Bachinger, J. (2018). Grain legume yields are as stable as other spring crops in long-term experiments across northern Europe. *Agronomy for Sustainable Development*, *38*, Article 63. https://doi.org/10.1007/s13593-018-0541-3

Rotundo, J. L., & Westgate, M. E. (2009). Meta-analysis of environmental effects on soybean seed composition. *Field Crops Research*, *110*(2), 147–156. https://doi.org/10.1016/j.fcr.2008.07.012

Rymuza, K., & Radzka, E. (2023). Analysis of trait stability of soybean cultivated under various environmental conditions. *Journal of Water and Land Development*, *59*(X-XII), 1–7. https://doi.org/10.24425/jwld.2023.147222

Sudarić, A., Simić, D., & Vratarić, M. (2006). Characterization of genotype by environment interactions in soybean breeding programmes of southeast Europe. *Plant Breeding*, *125*, 191–194. https://doi.org/10.1111/j.1439-0523.2006.01185.x

Tchebakova, N. M., Parfenova, E. I., Lysanova, G. I., & Soja, A. J. (2011). Agroclimatic potential across central Siberia in an altered twenty-first century. *Environmental Research Letters*, *6*, 045207. https://doi.org/10.1088/1748-9326/6/4/045207

Tukamuhabwa, P., Asiimwe, M., Nabasirye, M., Kabayi, P., & Maphosa, M. (2012). Genotype by environment interaction of advanced generation soybean lines for grain yield in Uganda. *African Crop Science Journal*, *20*(2), 107–115.

WRB. (2015). *World reference base for soil resources 2014, Update 2015. International soil classification system for naming soils and creating legends for soil maps* (World Soil Resources Report No. 106). FAO. https://www.fao.org/3/i3794en/I3794en.pdf

Yan, W., & Kang, M. S. (2002). *GGE biplot analysis. A graphical tool for breeders, geneticists, and agronomists* (1st ed.). CRC Press.

Yan, W., & Tinker, A. N. (2006). Biplot analysis of multi-environment trial data: Principles and applications. *Canadian Journal of Plant Science*, *86*, 623–645. https://doi.org/10.4141/P05-169

Yuan, K., Reckling, M., Ramirez, M. D. A., Djedidi, S., Fukuhara, I., Ohyama, T., Yokoyama, T., Bellingrath-Kimura, S. D., Halwani, M., Egamberdieva, D., & Ohkama-Ohtsu, N. (2020). Characterization of rhizobia for the improvement of soybean cultivation at cold conditions in central Europe. *Microbes Environ*, *35*(1), Article ME19124. https://doi.org/10.1264/jsme2.ME19124

Zimmer, S., Messmer, M., Haase, T., Piepho, H.-P., Mindermann, A., Schulz, H., Habekuß, A., Ordon, F., Wilbois, K.-P., & Heß, J. (2016). Effects of soybean variety and *Bradyrhizobium* strains on yield, protein content and biological nitrogen fixation under cool growing conditions in Germany. *European Journal of Agronomy*, *72*, 38–46. https://doi.org/10.1016/j.eja.2015.09.008

Zobel, R. W., Wright, M. J., & Gauch, H. G. (1988). Statistical analysis of a yield trial. *Agronomy Journal*, *80*(3), 388–393. https://doi.org/10.2134/agronj1988.00021962008000030002x


## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.


**How to cite this article:** Omari, R. A., Halwani, M., Reckling, M., Hua, M., & Bellingrath-Kimura, S. D. (2025). Environment and not genotype drives soybean yield stability in Northern Germany. *Agronomy Journal*, *117*, e70059. https://doi.org/10.1002/agj2.70059