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Rethinking seed sector performance indicators in Africa

Perspectives from factorial analyses on cross-country data

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Abstract

Effective seed sectors are essential for translating crop-improvement investments into productivity, resilience, nutrition, and welfare gains, yet evidence remains limited on how to measure seed-sector performance across countries and crops. This study assesses whether the Seed Sector Performance Index (SSPI) can be made more parsimonious, statistically grounded, and decision-relevant; whether complementary datasets capture dimensions omitted from the SSPI; and whether data-driven weighting and clustering improve country scores and classifications. We analyze the 2023 and 2025 SSPI rounds for up to 50 African countries; combine them with indicators from The African Seed Access Index and other sources; and apply principal component analysis, composite-index construction, hierarchical cluster analysis, multiple correspondence analysis, and sparse and robust principal component methods suited to small samples and missing observations. The first four principal components explain 72 percent of the variation in the augmented SSPI data, indicating substantial overlap among the 17 indicators. Reweighting indicators meaningfully changes some country scores and classifications, generally lowering scores where seed-import regulation, small-package availability, and support for farmer-managed seed systems, are weak. Complementary indicators—particularly seed-market concentration, research capacity and investment, regulatory conditions, support for farmer-managed systems, and participation in international seed-related regimes—add information not fully captured by the SSPI. Crop-specific results also reveal substantial within-country variation. These findings imply that governments, the African Union Commission, development partners, and private investors should use revised scores as diagnostic rather than definitive rankings, reassess fixed category thresholds, prioritize underrepresented seed-sector functions, and invest in regular country- and crop-specific data collection to guide breeding, regulation, market development, and seed-delivery investments.

Keywords: Seed Sector Performance Index, factor analysis, composite index, cluster analysis, Africa

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Acronyms and abbreviations

AGRA	Alliance for a Green Revolution in Africa;
ASTI	Agricultural Science and Technology Indicators
AUC	African Union Commission
BIC	Bayesian information criterion
CBD	Convention on Biological Diversity
DUS	distinctness, uniformity, and stability
EBA	Enabling the Business of Agriculture
EM-PCA	expectation-maximization principal component analysis
FMSS	farmer-managed seed systems
GDP	gross domestic product
ISSD	integrated seed sector development
ISTA	International Seed Testing Association
ITPGRFA	International Treaty on Plant Genetic Resources for Food and Agriculture
LASSO	least absolute shrinkage and selection operator
MCA	multiple correspondence analysis
OECD	Organization for Economic Co-operation and Development
PC	principal component
PCA	principal component analysis
QDS	quality-declared seed
R&D	research and development
ROSPCA	robust sparse principal component analysis
S-PCA	sparse principal component analysis
SeedSAT	Seed Systems Assessment Tool
SSA	Africa south of the Sahara
SSPI	Seed Sector Performance Index
TASAI	The African Seed Access Index
TLS	truthfully labeled seed
UPOV	International Union for the Protection of New Varieties of Plants
VRC	variety release committee.

1. Background

Seed sector capacity can affect whether investments in crop improvement actually translate into higher productivity, resilience, nutrition, and welfare in developing countries, including those in sub-Saharan Africa (SSA). An effective seed sector connects the development of improved varieties with seed multiplication, quality assurance, promotion, marketing, and distribution. These functions are shaped by crop biology, agroecology, institutions, markets, and farmer preferences. Disruptions at any stage within the seed sector can significantly lower the availability, accessibility, or affordability of quality seeds to farmers. Because seed sector constraints can differ across countries and crops, governments, development partners, breeding programs, and private firms need credible measures of how effective the seed sector is in each country to guide investment and policy decisions. Recently, several global and regional initiatives have responded to these needs, including the African Seed Access Index (TASAI, 2025), the Seed Systems Assessment Tool (SeedSAT) (AGRA, 2025), the World Bank's Enabling the Business of Agriculture (EBA) (World Bank, 2019), and the Access to Seeds Index (ASF, 2019). The Seed Sector Performance Index (SSPI), developed by TASAI, AGRA, and the African Union Commission, is by far one of the most comprehensive Africa-wide initiatives of this kind (AUC et al., 2024, 2026). The SSPI reports 17 standardized indicators for 47 SSA countries in 2023 and 50 SSA countries in 2025.

These emerging initiatives, including the SSPI, are major advances over fragmented country-level information and can help inform public spending, donor priorities, private investment, and regulatory reforms. However, the growing reliance on these seed-sector performance measures also makes their design consequential. Ideally, before an index is used to compare countries' seed sector performance levels, allocate scarce resources, or target breeding and delivery investments, it is important to assess what these indicators collectively measure and what they may omit. This is because composite indexes, such as SSPIs, can be sensitive to the selection of raw indicators, data quality, missing observations, and weighting rules (Ravallion, 2012; Dang et al., 2019; Jerven, 2013). These concerns are especially important for the seed sector, where formal, commercial, community-based, and farmer-managed subsystems interact in context-specific ways.

Specifically, we argue that the SSPI warrants further analysis along at least four aspects, even though it already provides a valuable and unusually broad evidence base. First, if several indicators convey overlapping information, a smaller set could preserve most of the index's informational content. Reducing overlap is important since collecting, updating, and validating 17 indicators across many countries can be resource intensive. Second, the current overall SSPI score is a simple average of the 17 indicators weighted equally regardless of their distinctiveness or degree of correlation with the others. Simple averaging can be a less informative dimension-reduction procedure than principal component analysis (PCA), in which observed covariance patterns are used to identify common dimensions and indicators that contribute more unique information. Third, the existing indicators may not fully represent certain elements of seed sectors, such as seed market structure, research capacity, regulatory conditions, international integration, or the extent of public support for farmer-managed seed systems. Fourth, country-level scores may hide substantial variation in seed-sector performance across crops.

This study, therefore, examines the 2023 and 2025 SSPI data together with additional indicators from TASAI and various other sources. The study addresses three questions. Can a smaller number of statistically derived dimensions capture most of the information contained in the 17 SSPI indicators? Do other seed-system-related datasets contain important dimensions not

currently captured by the SSPI? And can data-driven weighting and clustering improve overall scores and country classifications? We use PCA, composite index analysis, and cluster analysis, with sparse and robust variants suited to small samples and missing observations.

Our goal is to apply a more parsimonious and statistically grounded index that reduces redundancy, makes the basis for country scores more transparent, and improves the credibility of comparisons. These improvements matter because even modest changes in scores, rankings, or classifications may affect which countries, crops, and seed-sector functions receive attention and investment. The exercise can also inform the identification of a minimum set of indicators that is practical to update regularly while preserving information needed for cross-country and crop-specific decisions.

We contribute to various strands of the literature. Our analysis contributes to the research on seed system improvement in low- and middle-income countries (de Boef et al., 2024; Mausch et al., 2021; Takeshima et al., 2025a, b) by providing deeper discussions of seed sector performance measurement. Methodologically, it also contributes a new application of factorial analysis, dimension reduction, small-sample analysis, missing-data methods, and composite-index construction (see, for example, Hubert et al., 2005, 2016; Josse and Husson, 2013; Berlage and Terweduwe, 1988; Nicoletti et al., 2000; Nardo et al., 2005) to the literature.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 describes the data. Section 4 explains the methods, with additional technical detail in the appendixes. Section 5 presents the results. Section 6 concludes with policy and research recommendations.

2. Conceptual framework

Arguably, any measurement of a seed sector's performance in a given country or for a given crop requires sufficient grounding in theory to be credible and practical if it is to be relevant for public and private decision-making processes. In short, theory should drive what is measured. We draw on the integrated seed sector development theoretical framework first posited by Louwaars and De Boef (2012) and Louwaars et al. (2013).

The integrated seed sector development framing is based on the idea that crop reproductive biology, agroecological conditions, social and economic institutions, organizational arrangements and relationships, and preferences and behaviors of individuals and households shape a seed sector's functions, performance, and outcomes (de Boef et al., 2026). Key concepts that drive our deeper understanding of integrated seed sector development include pluralism of actors and their actions, iterative learning pathways and context-specific adaptation, and agency at the individual and community levels. This integrated framework is distinct from the rather limiting convention of separating commercial "formal" systems and farmer-managed "informal" systems that fail to recognize the myriad relationships between multiple seed systems, actors, institutions, and organizations that comprise a seed sector (Kilwinger et al., 2025; Spielman and Kennedy, 2016).[1] In the context of our study area, seeds and traits for very few crops are rarely developed and distributed solely by one modality. Rather, governmental, commercial, or community entities interact at some point in every seed system.

Our challenge is to somehow identify and measure the attributes and performance of an integrated seed sector. Measuring system outcomes—a task we save for future research—is relatively straightforward insofar as we can rely on standard indicators such as agricultural

[1] See De Boef et al. (2025, 2026) for an introduction and synthesis of these concepts set forth in a special issue of Agricultural Systems on integrated seed sector development.

production and productivity growth (increases in the quantity and value of agricultural output and yields), welfare (improvements in income, food security, well-being, or nutritional status), resilience (capacity to withstand production, price, and policy shocks), inclusion (measures of agency, empowerment, and equity), or environmental outcomes such as reductions in greenhouse gas emissions or increases in soil organic matter associated with new varieties and associated farming practices (de Boef et al., 2024, 2025; McGuire and Sperling, 2016). Measuring the components and functions of an integrated seed sector is much more difficult, and this difficulty poses the central challenge to this study. For example, there are no off-the-shelf indicators that measure the adaptive capacity of a highly localized, farmer-based seed system for roots, tubers, and bananas (Almekinders et al. 2019). Nor are there obvious and generalizable metrics that capture the effectiveness of the organizational relationships, networks, and collaborations that make public, private, or joint investment succeed (or fail) in building seed value chains (Etherton et al., 2025; Delaquis et al., 2024; Ter Steeg et al., 2024). Although it is beyond the scope of this study to collect new data on these and many other indicators of an integrated seed sector, we explore whether it is at all feasible to use available data to characterize integrated seed sector performance across countries and, to a lesser extent, across crops and crop archetypes.

3. Data and data sources

Data for this study are drawn from several sources; see Table 1 for a summary of data sources and country coverage. The primary dataset is the SSPI (AUC et al., 2024, 2026). The SSPI data consist of 17 indicators (described in the subsequent section) collected at the country level from 47 African countries in 2023 and again in 2025 for the original 47 countries and 3 new countries (50 SSA countries in total) through collaboration between the African Union, AGRA, and TASAI (AUC et al., 2024, 2026). All 17 indicators are standardized scores ranging from 0 (lowest) to 10 (highest), reported for each of the 50 countries, except for Comoros, Libya (missing 2 indicators), Seychelles, and Liberia (missing 1 indicator), and Cape Verde and Equatorial Guinea (missing all 17 indicators) in 2023. As explained in subsequent sections, our primary analyses on SSPI focus on the average values of the 17 SSPI indicators for 2023 and 2025. For countries with any missing SSPI indicators in 2023, we replace them with those reported in 2025.

The second data source is a dataset constructed from TASAI (2025) analysis, which contains various seed-sector-related information at the country level for 23 SSA countries as of 2025, documented in their respective country reports. The frequency of TASAI data collection varied across countries (ranging from the 5 rounds reported for Kenya and Uganda to just 1 round for various other countries), as did the set of data collected across rounds. For these multi-round variables from TASAI data, we use their average values across all rounds in our primary analyses because taking the averages can often mitigate measurement errors.

Crop-specific data are extracted from both 2023 and 2025 SSPI, as well as the TASAI reports. Both contain a small number of indicators that are disaggregated for the four major crops in a country, with the list of major crops naturally differing by country. These crop-specific data are used for supplementary analyses.

The TASAI and SSPI data are supplemented by additional seed-system-related data, including ASTI (2016) for agricultural R&D investment data, ISSD (Herpers et al., 2017) for more contextual data, and the World Bank (2025) for key development indicators. The data are also augmented with indicators on a country's membership status in various international agreements, schemes, standards, and organizations related to plant genetic resources, seeds, and

traits, including the International Treaty on Plant Genetic Resources for Food and Agriculture (ITPGRFA), the Nagoya Protocol on Access to Genetic Resources and the Fair and Equitable Sharing of Benefits Arising from their Utilization to the Convention on Biological Diversity,[2] the International Union for the Protection of New Varieties of Plants (UPOV), the Organisation for Economic Co-operation and Development (OECD) Seed Scheme, and the International Seed Testing Association (ISTA).

4. Methodology

To address the research questions articulated above, this study applies several statistical methods drawn from the family of factor analytic tools for data reduction, specifically PCA, cluster analysis, and composite index analysis to the augmented SSPI dataset. PCA has been widely used as a dimension-reduction tool to identify key components that characterize multidimensional data (Anderson, 1963; Jackson, 2003). We apply extensions of these methods to partly overcome challenges associated with our data, which are characterized by a relatively small sample size and the prevalence of missing observations. Specifically, we employ variants of the factor analytic tools, including sparse PCA (S-PCA)/robust-SPCA (see, for example, Hubert et al., 2005, 2016) to address small sample size and outliers, PCA-based imputation methods (see Josse and Husson, 2013) to address missing values, and multiple correspondence analysis (MCA) to address binary variables within a PCA framework. In this section, we describe the methodological approaches employed in this study and provide additional details in Appendix A.

4.1 Estimation of modified SSPI scores using composite index analysis for all 50 countries covered in the SSPI

4.1.1 PCA of SSPI variables and other related variables available for all 50 SSPI-studied countries

We first apply a standard PCA to 17 SSPI variables, as well as several additional non-SSPI variables available for all 50 SSPI-studied countries, for two purposes: to examine whether there are statistically significant correlations among variables such that a smaller number of variables could be used to capture the majority of variation underlying the 17 SSPI variables and to determine which variables may be relatively more distinct from other variables such that they might be assigned greater weight in evaluating the overall set of variables in the data.

For most countries in the sample, each of the 17 SSPI variables is available for both the 2023 and 2025 rounds. We primarily focus our analyses on the averages over these two rounds since taking averages can mitigate measurement error for each SSPI variable. Nonetheless, where relevant, we also conduct the same analyses using only the most recent (2025) round for comparison purposes.

In addition to the 17 SSPI variables, we add 2 non-SSPI variables: a variable from ISSD (Herpers et al., 2017) that captures support for the informal seed system, and another variable we synthesize to capture membership status in various global policy regimes. Since these non-SSPI variables are binary, and thus not directly suitable for PCA, and highly correlated among themselves, we first apply MCA to these sets of binary variables; predict key components among these binary variables, whereby these components are now continuous variables; and include in

[2]Membership in the Convention on Biological Diversity (CBD), predecessor to the ITPGRFA, the Nagoya Protocol, is excluded since all TASAI countries are CBD member countries.

PCA these MCA-predicted variables in place of the original binary variables.[3] Appendix Table 8 summarizes the results of MCA. Based on the results, we use the first predicted coordinates for each ISSD- and membership-related variable in the PCA.

4.1.2 Computation of modified SSPI scores based on PCA results from 4.1.1

The next step involves a composite index analysis initially developed for classification purposes by Berlage and Terweduwe (1988) and applied to the context of composite index development by Nicoletti et al. (2000) and Nardo et al. (2005). We term the resulting index a "Modified SSPI Score." The essential idea behind the composite index analysis is to compute an index as a weighted sum of (rotated) principal components (PCs), with weights reflecting contribution to overall variation of each PC, so that more dominant PCs receive greater weights. See Appendix A1 for more technical details of the approach.

4.1.3 Categorizations of countries based on modified SSPI and additional assessment through cluster analysis

While the continuous nature of the original and modified SSPI scores provides a high-resolution assessment of a country's seed sector performance, categorizing SSPI scores and countries into discrete groupings can render the scores more accessible and useful to decision-makers. For example, the first SSPI round categorized countries by dividing SSPI scores into 5 intervals (0–2, 2–4, 4–6, 6–8, 8–10; see AUC et al., 2024, 2026). We apply the same categorization to the modified SSPI scores and assess how significantly the modifications affect country categorization when compared to the original SSPI categorization.

A significant concern with such categorization is the potentially arbitrary nature of the cut-off points, that is, 2, 4, 6, and 8 in the case of the original SSPI. For example, it is possible for countries to be clustered around these cut-off points, implying relative similarity in seed sector performance but erroneously cast into different groups because of the cut-off points. To address this concern, we conduct additional assessments using cluster analysis to determine how well these cut-off points suit the data. Specifically, we apply hierarchical cluster analysis, which is advantageous for comparing results across different numbers of clusters because results with fewer clusters are not affected by those with more. We apply the average linkage method, which uses Euclidean distance-based similarity measures, as suggested to be effective in many situations and reasonably robust (Kaufman and Rousseeuw, 1990). Furthermore, we determine the optimal number of clusters using the commonly used Duda–Hart index (Duda and Hart, 1973).

4.2 Identification of key seed-sector variables not captured in the SSPI

Next, we expand our focus beyond the SSPI to identify whether other non-SSPI variables can potentially capture critical dimensions of seed system performance in SSA. Doing so involves mobilizing additional tools and methods to address some of the significant challenges, including small sample sizes and missing observations. We discuss these tools and methods below.

[3] Similar sequential steps using both MCA and PCA have been used in past studies, albeit in reverse order in the case of Costa et al. (2013). We take these sequential approaches because estimating MCA and PCA simultaneously becomes overly complicated if combined with sparse PCA.

4.2.1 Original set of variables considered

We first apply PCA to a combined dataset comprised of variables from the TASAI, SSPI, and supplementary indicators as described in Table 2. Variables in TASAI data are carefully selected to ensure their broad representation across key domains of the seed sector: (a) sector innovation; (b) sector structure and performance; and (c) sector policy and regulations. Variables are also selected among those with sufficient observations—specifically, no more than 20 percent, or four missing observations out of 23—so that those missing observations can be reliably recovered through imputation as described below. Several TASAI variables are also excluded when the same or closely related counterparts are included among the SSPI variables.

TASAI variables are supplemented by two variables on agricultural R&D investment from ASTI (2016); three binary variables from ISSD-Africa (Herpers et al., 2017), which proxy the integration of intermediate, farmer-managed systems within the seed systems; nine binary variables from World Bank's EBA studies, which proxy for the enabling environment for seed business; and the country membership status in seed-related global policy regimes. These supplementary variables are then combined with all 17 SSPI indicator variables. These variables are available for 50 African countries, including the 23 countries covered by the TASAI country studies.

The non-SSPI variables are also considered because they potentially capture seed-sector capabilities and outcomes that may be absent from, or only indirectly represented in, the SSPI. Among these, the TASAI variables cover three domains: sector innovation, sector structure and performance, and policy/regulations. Sector innovation is represented by the number of breeders per million hectares of the four focus crops in each country, and the average age of commonly used varieties. The first variable is standardized by crop area to approximate breeding capacity relative to the production scale. The second variable indicates the pace of varietal turnover, with prevalence of older varieties potentially signaling slower innovation or replacement speed. Where crop-specific values exist in TASAI reports, we average across the four country-specific focus crops, as indicated in Table 2.

For sector structure and performance, TASAI variables are intended to represent seed availability, seed market organization, seed-related service delivery, and farmers' physical and economic access to seed. They include the number of varieties sold per million hectares of focus crops; the combined market share of the four largest seed companies; the number of days needed to process seed imports; respondents' satisfaction with import processing, extension agents, and agrodealers per 1,000 agricultural households; satisfaction with extension services; and the average share of seeds sold in packages smaller than 2 kg across the four focus crops of each country. These variables are included because variety availability, market concentration, import efficiency, advisory and retail networks, and package size can jointly affect the sector competitiveness and farmers' access to seed. The satisfaction measures further capture how services and procedures function in practice.

For sector policy and regulation, TASAI variables measure the time required for variety release, satisfaction with the enforcement of seed laws/regulations, satisfaction with seed associations, satisfaction with seed inspection, and the number of public seed inspectors per million hectares of arable land. The seed association measures include the rating of seven dimensions of the association's functions, namely level of engagement in seed-sector issues, democratic decision-making, management, member value, advocacy, resource mobilization, and overall performance.

The two ASTI indicators measure agricultural research capacity and investment level, that is, full-time-equivalent agricultural researchers per 100,000 farmers and agricultural R&D spending as a share of agricultural GDP. They are included because the generation and adaptation of improved varieties depend on scientific personnel and sustained investment, dimensions that the SSPI captures only indirectly through the assessments of national breeding programs.

The ISSD indicators capture the levels of legal and institutional support for farmer-managed seed systems. These ISSD indicators record whether protocols exist for intermediate seed classes such as quality-declared seed or truthfully labeled seed, whether farmers may exchange and sell seed within farmer-managed systems, and whether farmers or civil society representatives participate in relevant seed-sector governance authorities. These are binary measures (yes / no) and are summarized by the first coordinate from MCA, a dimension-reduction tool similar to PCA but better suited to binary variables. The resulting MCA score represents the recognition of, and the institutional space for, farmer-managed systems, which is an important dimension of integrated seed sector development that may not be fully captured by a single SSPI indicator.

The World Bank's EBA variables describe the regulatory environment for variety registration, production, certification, and access to plant genetic materials. The variables are nine binary indicators that identify whether foreign variety registration or distinctness, uniformity, and stability testing is recognized; whether the variety release committee meets regularly; whether an updated variety catalogue is available in the country; whether private firms or third parties may produce early-generation seed or certified seed; whether certification fees are published; and whether legal procedures for accessing plant genetic material are specified. These provisions affect the predictability, cost, and market contestability of seed business activities. Because the indicators may be correlated and binary, the analysis uses the first three MCA coordinates, which together summarize most of the overall dispersion underlying these seven variables.

Finally, the membership variables identify whether a country participates in major seed-related global regulatory schemes, that is, the ITPGRFA, the Nagoya Protocol, UPOV, and the OECD Seed Schemes, and whether it has an ISTA-accredited seed testing laboratory. The first MCA coordinate summarizes these five indicators. These membership variables are included because participation in international treaties, intellectual-property and certification systems, and incorporation of international seed-testing standards to in-country testing facilities may improve access to genetic resources, regulatory harmonization, quality assurance, and regional or international seed trade.

Collectively, these non-SSPI variables allow the analysis to test whether research capacity, market structure, farmer-managed systems, regulatory implementation, and international integration contain information not significantly captured by the current SSPI.

4.2.2 Modification of standard PCA approaches to address small sample size, missing observations, and binary variables

We then apply PCA to the variables described in 4.2.1. In doing so, we apply various extensions to the standard PCA to address the unique challenges posed by the data in Table 2.

First, we develop a strategy to address the small sample size relative to the number of seed-sector variables. The number of variables in Table 2 is large relative to the sample size of countries (n=23). In this situation, standard PCA may fail to derive principal components reliably. A useful workaround is to apply sparse PCA (S-PCA) and its variants (see, for example,

Hubert et al., 2005, 2016; Erichson et al., 2020). The basic idea behind S-PCA is to modify standard PCA by penalizing the number of variables that have non-zero associations with each PC, so that PCs are identified more robustly using fewer essential variables. In this sense, the S-PCA approach is a subset of machine-learning-based shrinkage methods involving the least absolute shrinkage and selection operator (LASSO). See Appendix A2 for additional technical details on S-PCA.

In addition to the application of S-PCA, we apply an imputation approach to fill missing values for specific variables with PCA-derived estimates (see Serneels and Verdonck 2008; Josse and Husson 2013; Dray and Josse, 2015). Specifically, we apply PCA-based imputation to 23 TASAI-studied countries to impute certain variables that are missing. These variables include all non-SSPI variables in Table 2 where the number of observations is between 19 and 22, that is, variables for which no more than 20 percent out of 23 countries are missing.[4] See Appendix A3 for additional technical details.

In addition to applying MCA to ISSD-related variables and the policy regime membership-related variables mentioned above, we further apply MCA to the World Bank's EBA-related binary variables shown in Table 2. Based on the results of this exercise, we use the first through third predicted coordinates of the EBA-related variables in the PCA. Appendix Table 8 summarizes these results.

5. Results

5.1 Modified SSPI based on PCA and composite index analysis

5.1.1 Modified overall SSPI score for each country with all crops combined

We first present the results of a standard PCA applied to the 17 SSPI variables and the ISSD- and policy regime membership-related variables. As mentioned earlier, while our primary results are based on averages from the 2023 and 2025 SSPI data, we also present results based on the 2025 SSPI data only.

Figure 1 illustrates the estimated eigenvalues and the cumulative contributions of PCs as shares of the overall variation among variables, together with corresponding confidence intervals. The top-left panel of Figure 1 suggests that the first through fourth PCs are associated with point estimates of eigenvalues above 1, often used as a rule of thumb to determine whether a PC is relevant (see Kaiser 1958). The top-right panel of Figure 1 shows that the first PC explains 54 percent of the overall variation in the data and the first four PCs collectively explain 72 percent, a significant majority. Similar results shown in the bottom panels of Figure 1 generally hold when restricting the SSPI variables to those from the 2025 SSPI study.

Figure 2 illustrates the coefficients (loadings) for SSPI variables with respect to the four PCs.[5] Importantly, SSPI-8, SSPI-10, and SSPI-14 are among those that are relatively less correlated with other SSPIs (see Box 1 for a quick reference for the variables mentioned throughout this section). For example, SSPI-8 is correlated strongly positively with the third PC (Component 3), SSPI-10 is correlated strongly positively with the second PC, and SSPI-14 is

[4]As is described further in Appendix A3, related studies often find the imputation approaches reasonably reliable when no more than 20 percent of the samples are missing (Josse and Husson 2013; Dray and Josse 2015).

[5] Figure 2 shows "rotated" loadings, which adjust original unrotated loadings so that each SSPI is more clearly associated with one specific PC (Harman, 1976; Gorsuch, 1983).

strongly positively correlated with the fourth PC. Similarly, the ISSD-related variable is positively correlated with the fourth PC, supporting the inclusion of this variable.

Box 1: Variable quick reference

SSPI-8: Clarity and enforcement of seed import regulations

SSPI-10: Availability of seed in small packages

SSPI-14: Status of farmer-managed seed systems

The observed unequal contributions of different SSPI variables to each PC suggest that the original SSPI scores, which are a simple weighted average of all 17 SSPIs, can potentially be improved by modifying the SSPI score based on PC results using the composite index analysis approach of Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005) described earlier. Figure 3 and Figure 4 illustrate how the original SSPI scores compare with the modified SSPI scores based on the averages of the 2023 and 2025 SSPI scores, and based on the 2025 SSPI scores alone, respectively. A straight-line relationship would imply that the modified SSPI score perfectly matches the original SSPI score (the gray boxes correspond to the country categorization discussed in the following subsection). Both Figure 3 and Figure 4 show that, although there are positive correlations, the distributions of the modified SSPI scores differ noticeably from those of the original SSPI scores, indicating the former's potentially greater accuracy in measuring seed sector performance.

For countries that fall significantly below the straight line in Figure 3, including Benin (BEN), Guinea-Bissau (GNB), and Madagascar (MDG), original SSPI scores may overestimate seed sector performance. Although the reasons for differences from the original SSPI scores vary across countries, the overestimation is partly because these countries score relatively lower on SSPI-8, SSPI-10, and SSPI-14, that is, the variables associated with key PCs but underrepresented in the current SSPI. Some high-scoring countries, including Egypt (EGY), also show lower modified SSPI scores due to lower SSPI-14 scores. Due to similar mechanisms, a small number of countries lie above or close to the straight line, including Tanzania (TZA), Uganda (UGA), Sierra-Leone (SLE), and South Sudan (SSD). Many of these countries score relatively better on SSPI-8, SSPI-10, and SSPI-14, or on the ISSD-related variables.[6] Overall, the patterns in Figure 3 suggest the potential importance of accounting for unequal correlations among specific SSPIs when developing an overall SSPI score.[7]

[6] Modified SSPI is positively correlated with each SSPI, even though a fraction of loadings is negative, as shown in Figure 2. This is because the methods suggested by Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005) only use the information of the largest (rotated) loadings, and in our case, these largest loadings are positive for all SSPI.

[7] As described in the earlier section, the composite index approach used here involves rotating PCA. Importantly, as is mentioned in Appendix A1, aside from the approach by Kaiser (1958) which we used, there are numerous other ways to conduct PCA rotation. We therefore conduct robustness checks on the ways changes from the overall SSPI score remain relatively stable across different PCA rotation methods. As is shown in appendix Table 10, the patterns of the direction of changes from the overall SSPI score remain relatively stable across different PCA rotation methods. Therefore, our primary results based on Kaiser (1958) rotation methods are fairly robust.

It is also worth noting that the patterns of deviations from the original SSPI scores differ slightly between Figure 3 and Figure 4, underscoring the importance of distinguishing results based on the average of the 2023 and 2025 SSPI scores from results based only on the 2025 SSPI scores. Given the potentially smaller measurement errors, we prefer to place greater emphasis on Figure 3, which uses the averages of the 2023 and 2025 SSPI scores.

5.1.2 Categorizations of countries based on SSPI

We then proceed to the results of our typology analyses, which are implemented to assess the potential usefulness of developing discrete categories of countries beyond assigning continuous SSPI scores to each country. Table 3 summarizes country categories based on the original two-point/five-category approach used in the SSPI. These are applied to the 2023/2025 average SSPI scores (column (a)), its application to modified SSPI scores from subsection 5.1.1 (column (b)), and similar results based on the raw 2025 SSPI scores (column (c) and (d), respectively).

Each category is shown in the corresponding color schemes following the initial approach used in the 2023 SSPI: "Excellent" is indicated in green, "Good" in yellow-green, "Fair" in yellow, "Poor" in orange, and "Extremely Poor" in red. Mixed colors are applied to countries that may belong to categories based on a separate cluster analysis.

Results indicate that categorizations based on modified SSPI scores (column (b) and (d)) are somewhat different from those in columns (a) and (c). For example, in column (b) relative to column (a), Sudan, Côte d'Ivoire, and Madagascar drop from the 3rd group (yellow) to the 4th group (orange). Similarly, Somalia and Comoros drop to the 5th group (red).

In (d), further assessment based on cluster analysis suggests that additional countries—Malawi, Rwanda, Uganda, Eswatini, Ghana, and Nigeria—in the 2nd group (yellow-green) have SSPI scores that are only slightly above the cut-off (which is 6) and relatively closer to countries in the 3rd group (yellow) than to other countries in the 2nd group with higher SSPI scores, so that grouping these countries with other countries in the 3rd group (yellow) may be more sensible from a statistical standpoint. Figure 5 illustrates these further modified groups based on the cluster analysis. These patterns suggest that it may be worth reassessing, in future studies, the validity of setting an arbitrary cut-off level at 6, and that SSPI categories for countries like Malawi, Rwanda, Uganda, Eswatini, Ghana, and Nigeria should be interpreted with extra caution, even though these countries are categorized as having "Good" seed sector performance index values.

For reference, Table 9 in Appendix A5 shows similar groupings applied to the 2023 SSPI. While several countries, like Djibouti and Somalia, had somewhat different SSPI scores compared to the 2025 SSPI, the overall patterns of relations between the original and the modified groupings are similar. There are considerable deviations between the original and the modified SSPI scores, and generally more countries are categorized into lower groups.

5.1.3 Crop-specific SSPI: Illustrative results

While developing crop-specific SSPIs is challenging given the high degree of context-specificity associated with a given crop or crop archetype, it is interesting to see how the modified SSPI score reported earlier varies when we incorporate crop-specific information available in SSPI. These crop-specific variables are obtained by replacing the original values of certain SSPI variables, which are aggregated across crops for each country through weighted averages, for example, with crop-specific values of the SSPI variables when computing the

modified SSPI scores, as presented in subsection 5.1.1. Specifically, these SSPI variables include SSPI-2, SSPI-3, SSPI-5, SSPI-6, SSPI-7, and SSPI-10 (Box 2).[8] For all other SSPI variables, the same country-level values are used for all crops.

Box 2: Variable quick reference

SSPI-2: Number of varieties released in the last three years

SSPI-3: Adequacy of the national agricultural research institutes' breeding programs

SSPI-5: Adequacy of early generation seed

SSPI-6: Availability of varietal choice to farmers

SSPI-7: Utilization of quality commercial seed by farmers

SSPI-10: Availability of seed in small packages

Table 4 summarizes the crop-specific SSPI scores for major crops, while Figure 8 illustrates how updated crop-specific SSPI scores compare with the original crop-specific SSPI scores. While the values in Table 4 and Figure 8 should be interpreted with caution, they offer some indications of how the modified SSPI can potentially vary across crops for each country. Specifically, scores can sometimes differ by about 1.0 between crops (for example, Maize (6.26) vs. Sorghum (5.20) in Ghana, Maize vs. Sorghum in Nigeria, or Maize vs. other crops in Zambia). Additionally, there are no clear crops that consistently score higher than other crops, which suggests that the variations of SSPI scores across crops can be country specific. For example, while maize scores are relatively higher in Burundi, Kenya, Rwanda, and Zambia, they are considerably lower in Botswana, Madagascar, and Namibia, among others. These patterns suggest that continuous efforts in improving SSPI for specific crops will be critical.

5.2 Identification of key seed-sector variables not captured in the SSPI (among 23 TASAI countries that report both SSPI and TASAI)

We now turn to the results of S-PCA described in subsection 4.2.2, which is intended to shed light on which other key seed-sector variables can be included in future SSPI data collection efforts. Table 5 presents the four principal components and the variables that remain influential as the estimation process narrows down the list of potential variables. This is presented as a progression of results in column (a) to columns (b) and (c).[9]

[8] A majority of crop-specific SSPI scores in Table 4 are slightly lower than the overall SSPI scores, primarily because of how SSPI-2 and SSPI-6 are treated in the overall SSPI. Specifically, SSPI-2 and SSPI-6 are based on (kinked linear transformations of) the *total* number of varieties across all four focal crops of the country (AUC et al., 2024, Tables 5 and 6). SSPI-2 and SSPI-6 for each crop are always smaller than the total of all four crops and thus lead to slightly lower crop-specific SSPI scores. We simply applied the same kinked linear transformations to individual crops, given the difficulty in identifying suitable crop-specific transformation formulas.

[9] Table 5 presents the first 4 principal components (PC), coefficients of selected variables in each PC, and eigenvalues for each PC. Each set of results is shown for 3 levels of LASSO-penalization parameter λ; the optimal value of λ (1.5) selected by the methodology suggested by Croux et al. (2013) and Hubert et al. (2016), a less penal

Table 5 offers several findings of note. First, quite a few variables from TASAI and other non-SSPI variables are found to be significant elements of the first PC and other PCs, in addition to variables that are solely included in the SSPI, that is, SSPI PC1 through SSPI PC6 in the rows toward the bottom. These patterns imply that the current SSPI can be generally improved by incorporating various seed system-related variables not currently captured, including number of researchers per 100,000 farmers, Agricultural R&D spending as a share of Agricultural GDP, ISSD MCA variables which capture the support for informal seed systems, EBA MCA variables that relate to regulatory policies and institutions for enabling the seed-sector business, and membership to various international treaties (ITPGRFA, Nagoya Protocol, UPOV, OECD Seed Scheme, and ISTA).

Second, among these non-SSPI variables, certain variables are found to be relatively more persistently selected as key elements of the PCs. These include market concentration, the ISSD MCA variable, and the EBA MCA variables, which are often found to be key elements of the first principal component (PC1) and are selected persistently across a broad range of the values of λ. These patterns suggest that there are subsets of non-SSPI variables that are robustly key and are particularly important to consider when improving SSPI.

5.3 Model consistency and alignment with the integrated seed sector development framework

Finally, we explore whether the parsimonious set of indicators and the resulting scoring are consistent with the integrated seed sector development framework described earlier. Our results suggest that the statistical improvements generated with the analysis set forth above also reflect the inclusion of several indicators that better capture elements of an integrated seed sector development framework. These include variables related to support for informal seed systems (ISSD MCA variable) regulatory policies and institutions that enable private-sector access to varieties and seed production activities (EBA MCA variables), for example. Regarding the latter, while SSPI captures many of these aspects of private-sector seed production based on specific scoring rules and experts' opinions, EBA's scoring approach based on yes/no answers to various aspects of regulatory policies and institutions (as described in Table 2) may capture a new set of information that is not fully captured by SSPI. Importantly, the crop-specific analysis suggests further opportunities for improvement that are consistent with the crop- and context-specificity that underpins the integrated seed sector development approach. In other words, efforts to characterize seed sector performance require a fine paintbrush rather than broad brushstrokes.

6. Policy recommendations and concluding remarks

Proxy indicators that measure seed sector performance in SSA are critical to the prioritization of both public and private investments in crop improvement and the delivery of genetic gains to farmers. In an era of increasingly scarce resources for development assistance and competing demands on those resources, it is incumbent on governments and their development partners to set priorities based on credible and timely data and analysis. This study makes a small but hopefully significant contribution to this space.

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value of $\lambda = 1.0$, and a more penal value of $\lambda = 2.0$. As is one of the prominent features of S-PCA, coefficients for certain variables are set as exactly 0, unlike in a standard PCA result, which allows us to identify a narrower set of variables that explain the overall variation in seed sector-related indicators. The footnote in Table 5 describes in detail the specifications used in the S-PCA. Eigenvalues in the bottom row suggest that all PCs satisfy eigenvalue ≥ 1.

Realizing economic, social, and environmental gains from crop improvement requires more than just efficient and effective breeding programs, whether run by public research organizations, private companies, or farmer-based organizations. It also requires a system through which quality seed of well-adapted varieties is promoted, marketed, and distributed to farmers. There is little sense in breeding new varieties without channels to the farmers who ultimately plant those varieties.

But the channels to those farmers are many and varied, which is why this study grounds itself in the framing of an integrated seed sector development. While the performance of formal, commercial channels may be relatively easy to measure, namely through numbers of new varieties released or quantities of certified seed sold, there rarely exists a formal system that is not somehow integrated with an informal system. But measuring attributes of informal systems, for example, whether women and men smallholder farmers have voice and agency in seed system policy formulation, or whether farmer-based organizations are empowered and capacitated to produce certain classes of seed, is challenging.

Prior efforts by TASAI, the AUC, AGRA, ISSD, the World Bank, and others have shed new light on what can be measured. Our study takes this work one step further by analyzing their data in-depth to enhance the relevance and credibility of the insights and recommendations that can be drawn from their work. This effort requires a careful balancing act in which we ensure representativeness across key dimensions of seed sector performance while also maintaining simplicity that allows for cross-country and crop-specific comparisons.

Our findings suggest that for a majority of SSA countries, a modified overall SSPI score derived as a composite index based on PCA is considerably lower than the original overall SSPI score computed with simple averages, suggesting that the original overall SSPI score may overestimate the seed sector performance for many SSA countries. A closer examination indicates that overestimation is likely due to the fact that many countries score relatively lower for SSPI variables that are important but underrepresented (for example, the Clarity and enforcement of seed import regulations (SSPI-8), availability of seed in small package sizes (SSPI-10), and the support for farmer-managed seed systems (SSPI-14)), while they score higher for those that are overrepresented (for example, SSPI-1, SSPI-3, SSPI-15, SSPI-17 which are generally highly correlated with other SSPIs).

Our findings also suggest that the original two-point/five-category approach used in the SSPI generally matches well with the way countries cluster around similar SSPI scores, but some countries in the bottom range of original categories may be more similar to and better clustered with those in the lower categories than with those in the upper range of the same categories. In turn, the current threshold separating categories (SSPI score = 2, 4, 6) may require reevaluation.

At the same time, the application of sparse- and robust-PCA to an expanded set of non-SSPI variables available for a smaller set of countries suggests that there are still various key seed sector variables not currently included in SSPI, like seed market concentration and the ISSD and EBA-related indicators.

Our findings offer several implications and opportunities for public policy. First, and most obvious, is the need for continued investment in seed sector development given the considerable variance in performance across countries, which is reflected in both the original datasets used in our analysis and in the findings from our own analysis. Second is the need for greater investment in seed sector functions corresponding to clarity and enforcement of seed import regulation (SSPI-8), increased availability of seed in small package sizes (SSPI-10), and support for farmer-managed seed systems (SSPI-14), all of which are scored relatively low for

many countries and yet have received less attention due to their underrepresentation in the latest SSPI. Third, and noting that it is beyond the scope of this study to identify causal relationships, there is a need for further investigation of the significant relationships between the variables used in or adjacent to this analysis. A clear example of this is our result indicating that seed market concentration explains a fair amount of variance in sector performance. This suggests an opening to investigate whether reductions in market concentration through support for more decentralized, smaller-scale seed producers can lead to higher rates of utilization of quality commercial seed.[10] Another example is more along the lines of the "proof-is-in-the-pudding" argument,[11] which is whether SSPI scores (or changes in the scores) explain variation in agricultural productivity and other outcomes of interest (or changes in these outcomes over time) with an acceptable level of model consistency and econometric rigor. Fourth is the opportunity for South–South learning that emerges from our validation of these scores. Noting the importance and cross-country variation in seed import regulation (SSPI-8), small seed packaging (SSPI-10), and farmer-managed seed systems (SSPI-14), there are opportunities for cross-country learning led by countries that score relatively higher on the policies and practices that led to their higher indicator scores. Examples include Kenya, Namibia, Rwanda, and Tanzania for SSPI-10, and Ethiopia and Tanzania for SSPI-14.

Finally, we would suggest that the modified scores provided here can be used as a credible input into decision-making on which countries and which activities governments and their development partners should prioritize for further investment. Where countries have made limited investments in seed sector development but have well-performing breeding programs, there is an opportunity to reallocate attention to the former through strategic policies and programs in capacity development, regulatory reforms, agricultural extension services, and market systems. Where countries have made limited investments in breeding programs but have well-performing seed systems, then there is an opportunity to increase investment in breeding programs (or participation in breeding networks for smaller countries if it is difficult to achieve economies of scale in breeding).

We conclude by highlighting the continued need for comprehensive country- and crop-specific data on seed sector performance that captures the key integrated dimensions of seed sector development in SSA countries. This is a task that requires a considerable degree of agility because, as our analysis suggests, the region's seed systems are evolving, such that many of the conventional indicators that were built into previous data collection initiatives and thus are weaker predictors of observed variation in seed sector performance. There is considerable value in continued efforts to collect better data, conduct deeper analyses, and investigate the causal relationships between seed sector performance and broader development outcomes in SSA and other low- and middle-income countries.

[10] See, for example, Mekonnen et al. (2026) on the impact of Ethiopia's direct seed marketing approach that incentivized private sector entry into the market for maize and wheat seed.

[11] We thank Willem Janssen for introducing this term in a prior study on country-level performance indicators, indexes, and scoring related to agricultural innovation systems.

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Table 1. Data and coverage across countries

Country Code	Country	SSPI 2023	SSPI 2025	TASAI	Other related indicators			
					ASTI	ISSD 2017	EBA	Member status[a]
AGO	Angola	x	x			x	x	x
BEN	Benin	x	x		x	x	x	x
BWA	Botswana	x	x		x	x		x
BFA	Burkina Faso	x	x	x	x	x	x	x
BDI	Burundi	x	x	x	x	x	x	x
CMR	Cameroon	x	x		x	x	x	x
CPV	Cape Verde		x		x	x		x
CAF	Central African Republic	x	x		x	x		x
TCD	Chad	x	x		x	x		x
COM	Comoros	x	x			x		x
COG	Congo, Republic of the	x	x		x	x		x
CIV	Côte d'Ivoire	x	x		x	x	x	x
DRC	Congo, Dem. Republic of	x	x	x	x	x	x	x
DJI	Djibouti	x	x			x		x
EGY	Egypt	x	x		x	x	x	x
GNQ	Equatorial Guinea		x			x		x
ERI	Eritrea	x	x		x	x		x
SWZ	Eswatini	x	x		x	x		x
ETH	Ethiopia	x	x	x	x	x	x	x
GAB	Gabon		x		x	x		x
GMB	Gambia	x	x		x	x		x
GHA	Ghana	x	x	x	x	x	x	x
GIN	Guinea (Conakry)	x	x		x	x	x	x
GNB	Guinea-Bissau	x	x		x	x		x
KEN	Kenya	x	x	x	x	x	x	x
LSO	Lesotho	x	x		x	x		x
LBR	Liberia	x	x	x	x	x	x	x
LBY	Libya	x	x			x		x
MDG	Madagascar	x	x	x	x	x	x	x
MWI	Malawi	x	x	x	x	x	x	x
MLI	Mali	x	x	x	x	x	x	x
MRT	Mauritania	x	x		x	x		x
MOZ	Mozambique	x	x	x	x	x	x	x
NAM	Namibia	x	x		x	x		x
NER	Niger	x	x	x	x	x	x	x
NGA	Nigeria	x	x	x	x	x	x	x
RWA	Rwanda	x	x	x	x	x	x	x
SEN	Senegal	x	x	x	x	x	x	x
SYC	Seychelles	x	x					x
SLE	Sierra-Leone	x	x	x	x	x	x	x
SOM	Somalia	x	x	x		x		x
ZAF	South Africa	x	x	x	x	x	x	x
SSD	South Sudan	x	x	x		x		x
SDN	Sudan	x	x		x	x	x	x
TZA	Tanzania	x	x	x	x	x	x	x
TGO	Togo	x	x		x	x	x	x
TUN	Tunisia	x	x			x	x	x
UGA	Uganda	x	x	x	x	x	x	x
ZMB	Zambia	x	x	x	x	x	x	x
ZWE	Zimbabwe	x	x	x	x	x	x	x

Source: Authors' compilations.

Notes: TASAI = The African Seed Access Index; SSPI = Seed Sector Performance Index; ASTI = Agricultural Science and Technology Indicators; ISSD = Integrated Seed Sector Development (Herpers et al., 2017); EBA = Enabling the Business of Agriculture. [a] Variables indicating whether the country is a member/signatory of each of The International Treaty on Plant Genetic Resources for Food and Agriculture (ITPGRFA), the Nagoya Protocol on Access and Benefit-sharing, the International Union for the Protection of New Varieties of Plants (UPOV), the OECD Seed Scheme, and the International Seed Testing Association (ISTA).

Table 2. Seed sector variables used in principal component analysis

Variables	Unit	No. of obs.	Mean (std dev)
TASAI data			
Sector Innovation (Domain 1)			
Number of breeders per 1 million ha of four major crops[a]	No.	23	0.660 (0.681)
Age of commonly used varieties[a]	No.	22	14.947 (6.963)
Sector structure and performance (domain 2)			
# of varieties sold in a year	No. per million ha of focus crops	19	0.616 (0.621)
Market concentration - share of top four seed companies/producers[a]	%	23	76.959 (14.518)
Seed imports - processing time (days)	Number	21	18.847 (11.649)
Seed imports - processing time (satisfaction rating)	Score (0 - 100)	18	60.762 (15.045)
Extension agents - Ratio to agricultural households	No. (in 1,000)	23	3.499 (5.817)
Extension agents - Industry opinion rating (0 - 100)	Score (0 - 100)	23	52.574 (15.457)
Agrodealers - Ratio to agricultural households	No. (in 1,000)	21	9.579 (11.603)
Share of seed sold in small packages < 2kg[a]	%	23	24.075 (22.348)
Policy and regulations (domain 3)			
Variety release - Length (months)[a]	No.	23	26.390 (9.126)
Satisfaction with the enforcement of seed law/regulations (opinion)	Score (0 - 100)	18	63.144 (14.843)
Seed association satisfaction	1st PC of 7 variables	20	
1. Activity on important seed sector issues	(satisfaction rating		66.245 (14.843)
2. Democracy in the elections and decision making	scores 0 – 100)		69.820 (15.548)
3. Managerial ability			63.930 (12.505)
4. Providing value to members			63.540 (13.479)
5. Effectiveness in advocacy			64.810 (11.832)
6. Ability to mobilize resources			58.080 (13.232)
7. Overall rating			64.620 (11.481)
Seed inspections - Industry opinion rating (satisfaction rating)	Score (0 - 100)	23	65.343 (15.619)
Number of seed inspectors (public) per million ha of arable land	No.	22	8.391 (6.416)
Other related variables			
Number of researchers (full time equivalent) per 100,000 farmers	No.	21 for TASAI-studied countries (41 for SSPI-studied countries)	17.038 (26.915)
Ag R&D spending as a share of AgGDP	%		0.675 (0.750)
Informal seed system indicator based on ISSD (Herpers et al., 2017)	1st MCA score of 3 variables (0/1)	23 for TASAI-studied countries (50 for SSPI-studied countries)	
1. Protocols exist for seed classes such as QDS or TL seeds? (yes = 1)			0.286 (0.456)
2. Freedom to exchange and sell seed within FMSS? (yes = 1)			0.306 (0.466)
3. Farmers or civil society members included in authorities? (yes = 1)			0.490 (0.505)
Quality of seed regulation index, within the Enabling the Business of Agriculture indicator based on World Bank (2019)	3 MCA scores of 9 variables (0/1)	21 for TASAI-studied countries (30 for SSPI-studied countries)	

Variables	Unit	No. of obs.	Mean (std dev)
1. If a variety is already registered in another country, does the law allow it to be automatically approved for commercialization? (yes = 1)			0.433 (0.504)
2. Are distinctiveness, uniformity and stability (DUS) testing data from foreign authorities accepted? (yes = 1)			0.300 (0.466)
3. In practice, does the variety release committee (VRC) meet on demand or at least once per growing season? (yes = 1)			0.600 (0.498)
4. Is there a catalogue listing registered varieties? (yes = 1)			0.733 (0.450)
5. Is the variety catalogue updated at least once per growing season? (yes = 1)			0.300 (0.466)
6. Can private seed companies or third parties produce "early generation seed" from public varieties? (yes = 1)			0.867 (0.346)
7. Can private seed companies or third parties (for example, private laboratories) certify seed? (yes = 1)			0.433 (0.504)
8. Does the national seed authority publish a fee schedule for seed certification costs? (yes = 1)			0.567 (0.504)
9. Does the law prescribe the procedural requirements to access plant genetic materials? (yes = 1)			0.367 (0.490)
Membership-related indicator	1st MCA score of 5 variables (0/1)	23 for TASAI-studied countries (50 for SSPI-studied countries)	
1. Signatory of ITPGRFA (Plant Treaty) (yes = 1)			0.898 (0.306)
2. Signatory / Party to the Nagoya Protocol (yes = 1)			0.939 (0.242)
3. Membership with UPOV (yes = 1)			0.143 (0.354)
4. OECD Seed Schemes (yes = 1)			0.224 (0.422)
5. Presence of ISTA accredited labs (yes = 1)			0.245 (0.662)

SSPI data			Average of 2023/2025
SSPI-1: Quality of the variety release and registration process	Score (0 – 10)	50	5.196 (2.848)
SSPI-2: Number of varieties released in last 3 years	Score (0 – 10)	50	3.167 (2.852)
SSPI-3: Adequacy of NARIs	Score (0 – 10)	50	3.746 (1.931)
SSPI-4: Status of the national program on Plant Genetic Resources for Food and Agriculture	Score (0 – 10)	50	4.850 (2.274)
SSPI-5: Early Generation Seed – Adequacy	Score (0 – 10)	50	5.678 (2.074)
SSPI-6: Availability of crop varietal choice to farmers	Score (0 – 10)	50	3.860 (2.488)
SSPI-7: Utilization of quality commercial seed - proportion to national seed requirements	Score (0 – 10)	50	3.239 (2.740)
SSPI-8: Clarity and enforcement of seed import/export regulations	Score (0 – 10)	50	6.669 (2.168)
SSPI-9: Agro-dealer networks adequacy	Score (0 – 10)	50	4.777 (2.362)
SSPI-10: Availability of seed in small package sizes	Score (0 – 10)	50	2.705 (2.803)
SSPI-11: Status of national seed policy instruments	Score (0 – 10)	50	7.238 (2.463)
SSPI-12: Status of alignment of national seed policy instruments with harmonized regional seed regulations	Score (0 – 10)	50	6.189 (2.644)
SSPI-13: Status of adoption of national biosafety frameworks to guide plant breeding and seed production	Score (0 – 10)	50	4.846 (3.109)
SSPI-14: Status of FMSS in national seed policy instruments and institutional arrangements	Score (0 – 10)	50	3.443 (2.682)
SSPI-15: Adequacy of seed inspection services	Score (0 – 10)	50	4.746 (2.370)
SSPI-16: Counterfeit seed - Adequacy of government efforts to combat counterfeit seed	Score (0 – 10)	50	5.105 (2.326)
SSPI-17: Adequacy of the national seed trade association	Score (0 – 10)	50	4.228 (3.268)

Source: Authors.

Notes: FMSS = Farmer-Managed Seed Systems; MCA = Multiple Correspondence Analysis; PC = Principal Component; SSPI = Seed Sector Performance Index. [a] Average across 4 country-specific focus crops defined in TASAI data. [b] Weighted average across 4 country-specific focus crops (weighted by volume)

Table 3. Modified SSPI categories of 50 countries (2025 SSPI, 2023/2025 average SSPI)[a, b]

Country	Based on 2023/2025 average SSPI		Based on 2025 SSPI	
	(c) Original SSPI scores	(d) Modified SSPI scores in Figure 3	(a) Original SSPI scores	(b) Modified SSPI scores in Figure 4
South Africa	8.63	8.38	8.64	8.66
Zambia	7.86	7.56	7.83	7.47
Egypt	7.62	7.01	8.13	7.61
Zimbabwe	7.41	7.07	7.62	7.29
Kenya	7.39	7.31	7.64	7.40
Tanzania	7.30	7.56	7.35	7.32
Ethiopia	6.67	6.66	7.26	7.12
Malawi	6.45	6.12	6.43	5.98
Rwanda	6.39	6.34	6.72	6.39
Tunisia	6.35	6.32	6.92	7.04
Uganda	6.30	6.47	6.12	6.10
Eswatini	6.26	5.96	6.38	6.03
Ghana	6.25	6.04	6.58	6.24
Nigeria	6.22	5.99	6.15	5.83
Mali	5.79	5.21	5.85	5.08
Burkina Faso	5.75	5.22	5.73	5.29
Benin	5.68	4.97	5.99	5.30
Burundi	5.33	5.17	4.87	4.61
Togo	5.24	4.7	4.9	4.31
Senegal	5.20	4.87	5.1	5.04
Niger	5.20	4.85	4.83	4.42
Cameroon	5.15	5.08	4.86	4.79
Botswana	4.79	4.54	4.02	4.00
Gambia	4.53	4.34	4.18	3.99
Sudan	4.37	3.76	4.08	3.48
Mozambique	4.36	4.21	4.8	4.5
Côte d'Ivoire	4.36	3.76	4.39	3.75
Madagascar	4.25	3.66	3.98	3.57
Namibia	4.22	3.99	4.24	3.95
Sierra-Leone	4.10	4.41	3.76	3.69
Chad	3.86	3.37	3.68	3.1
Eritrea	3.84	3.61	4.05	3.85
Seychelles	3.76	3.27	3.61	3.28
Guinea-Bissau	3.59	2.88	3.08	2.47
Liberia	3.57	3.5	3.94	3.61
DRC	3.54	3.16	3.27	3.03
Angola	3.52	3.28	3.73	3.15
Lesotho	3.14	2.62	2.75	2.32
Mauritania	3.03	2.54	3.24	2.69
Djibouti	2.94	2.5	4.53	4.29
South Sudan	2.80	3.16	3	3.26
Cape Verde	2.71	2.45	2.71	2.1
Guinea	2.68	2.78	1.88	1.82
Libya	2.65	2.58	2.55	2.46
Somalia	2.29	2.22	3.01	3.08
Comoros	2.29	2.02	2.4	2.4
Gabon	1.96	1.91	1.96	1.71
Central African Rep.	1.84	1.86	1.48	1.32
Congo, Rep. of	1.77	1.7	1.56	1.44
Equatorial Guinea	0.00	0.05	0	0.04

Source: AUC et al. (2024, 2026) for Overall SSPI scores; Other figures are based on authors' analyses.

Notes: [a] Coloring corresponds to "Excellent" (Green), "Good" (Yellow-Green), "Fair" (Yellow), "Poor" (Orange) and "Extremely Poor" (Red) in AUC et al. (2024, 2026).

Table 4. Illustrative results on crop-specific SSPI scores (for major crops) using 2023/2025 average SSPI

Country	Country	Original SSPI scores (2023 - 2025 average)	Modified SSPI scores (2023 - 2025 average)	Crop specific overall SSPI scores								
				Maize	Beans	Cow-pea	Groun d nut	Millet	Rice	Sorg-hum	Soya beans	Wheat
AGO	Angola	3.52	3.29	3.36	3.18				3.37		2.92	
BDI	Burundi	5.33	5.16	5.11	4.36				4.46			
BEN	Benin	5.68	5.01	5.09					4.83		4.87	
BFA	Burkina Faso	5.75	5.26	5.23				4.93	5.10	4.96		
BWA	Botswana	4.79	4.56	3.95		4.66		4.45		4.10		
CAF	Central African Rep.	1.84	1.85	1.98	1.84		1.71			1.71		
CIV	Côte d'Ivoire	4.36	3.75	3.88					3.71			
CMR	Cameroon	5.15	5.06	4.99					5.04	4.64		
COG	Congo, Rep.	1.77	1.71	1.77			1.64					
COM	Comoros	2.27	2.02									
DJI	Djibouti	2.94	2.52									
DRC	DRC	3.54	3.17	3.04					2.98			
EGY	Egypt	7.62	7.02	6.55					5.82			6.01
ERI	Eritrea	3.84	3.71					3.54		3.58		3.80
ETH	Ethiopia	6.67	6.62	6.25						6.13		6.46
GAB	Gabon	1.96	1.91	1.87								
GHA	Ghana	6.25	6.05	6.26					5.55	5.20	5.33	
GIN	Guinea	2.68	2.79	2.66			2.77		2.78			
GMB	Gambia	4.53	4.33	4.42			4.07	3.90	4.39			
GNB	Guinea-Bissau	3.59	2.93	3.07				2.78	2.93	3.02		
KEN	Kenya	7.39	7.32	7.40	6.70	6.40				6.90		
LBR	Liberia	3.57	3.50	3.46		3.27	3.28		3.61			
LBY	Libya	2.65	2.63									2.52
LSO	Lesotho	3.14	2.67	2.68	2.80					2.51		2.39
MDG	Madagascar	4.25	3.63	3.07	3.74		3.64		3.64			
MLI	Mali	5.79	5.18	4.69				4.25	4.91	4.81		
MOZ	Mozambique	4.36	4.19	4.27		4.20	4.12		4.12			
MRT	Mauritania	3.03	2.52	2.23		2.23			2.80	2.23		
MWI	Malawi	6.45	6.14	6.09	5.49		5.34				5.73	
NAM	Namibia	4.22	4.03	3.58		4.24		3.89		4.05		
NER	Niger	5.20	4.82	5.27		4.62		4.70		4.66		
NGA	Nigeria	6.22	6.00	6.00		5.16			5.53	5.03	5.03	
RWA	Rwanda	6.39	6.28	6.33	5.12							
SDN	Sudan	4.37	3.79				3.46	3.50		3.84		4.12
SEN	Senegal	5.20	4.83	4.02			4.08	4.13	4.02			
SLE	Sierra-Leone	4.10	4.39	4.37			4.34		4.45	4.51		
SOM	Somalia	2.29	2.21	2.31		2.04				2.10		
SSD	South Sudan	2.80	3.09	3.40			2.69			3.10		
SWZ	Eswatini	6.26	5.97	5.61	5.70		5.14					
SYC	Seychelles	3.76	3.34									
TCD	Chad	3.86	3.36				3.23	3.38		3.32		
TGO	Togo	5.24	4.71	4.57					4.46	4.36	4.60	
TUN	Tunisia	6.35	6.36									5.88
TZA	Tanzania	7.30	7.56	7.46	7.02				6.92			
UGA	Uganda	6.30	6.47	6.57	6.08							
ZAF	South Africa	8.63	8.41	7.94							7.78	7.58
ZMB	Zambia	7.86	7.58	7.71					6.72		6.64	6.78
ZWE	Zimbabwe	7.41	7.09	6.93						6.53	6.44	6.40

Source: Authors' computations.

Table 5. Results of sparse principal component analysis applied to the 23 TASAI-studied countries[a, b]

Variables	Level of penalization parameters (λ; larger λ = more parsimonious results)											
	(a) λ = 1.00				(b) Model selected λ (λ = 1.50)				(c) λ = 2.00			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
# of varieties sold in a year	0.019	–0.072										
Age of commonly used varieties	–0.201	0.159	0.207		–0.257							
Market concentration	0.336		0.115		0.238						1.000	
Seed imports - processing time (days)							1.000					
Seed imports - processing time (satisfaction)	0.137		0.658									
Variety release - Length (months)	–0.163	0.570										
Enforcement of seed law/regulations	0.069		–0.018									
Seed association satisfaction	0.449		0.107		0.377							
Seed inspections satisfaction												
Extension agents - Ratio to ag household	–0.282	0.081	0.294									
Extension agents - satisfaction												
Agrodealers - Ratio to ag household		0.038	0.557									
Number of researchers per 100,000 farmers		0.014		–0.036	0.147	–0.042						
Ag R&D spending as a share of AgGDP	0.144	–0.086			0.304							
number of breeders per 1 million ha	0.103	–0.060										
Number of seed inspectors	–0.097	–0.043										
ISSD MCA variable	–0.436	–0.189	–0.076		–0.309							
EBA MCA variable 1	0.296	0.104			0.428	0.009						
EBA MCA variable 2	–0.142											
EBA MCA variable 3		–0.211		0.526		0.121						1.000
Membership MCA variable	–0.178	–0.411	0.172		–0.398	–0.002						
SSPI PC 1[c]	0.256	0.137	–0.249		0.423	0.003						
SSPI PC 2[c]	0.024	0.181										
SSPI PC 3[c]				0.658		0.730				1.000		
SSPI PC 4[c]	–0.184	0.481						1.000				
SSPI PC 5[c]	0.162				0.074							
SSPI PC 6[c]	0.135	0.196	0.078									
Eigenvalues	5.427	2.728	2.456	1.305	3.851	2.483	1.321	1.084	1.562	1.154	0.914	0.826

Source: Authors.

Notes: [a] R-software command `rospca` (Hubert et al., 2016) is used for the analysis with the following specification; $k = 0$, $k_{Max} = 28$, $\alpha = 0.75$ (default), h-parameter = "NULL" (default), ndir = "all", grid = "TRUE" (default), stand = "TRUE" (default), skew = "FALSE" (default). [b] EBA = Enabling Business in Agriculture; MCA = Multiple Correspondence Analysis; PC = Principal Component; R&D = Research and Development; SSPI = Seed Sector Performance Index; [c] These SSPI PCs are based on the averages between 2023 and 2025 for each SSPI variable (instead of solely using 2025 SSPI variable).

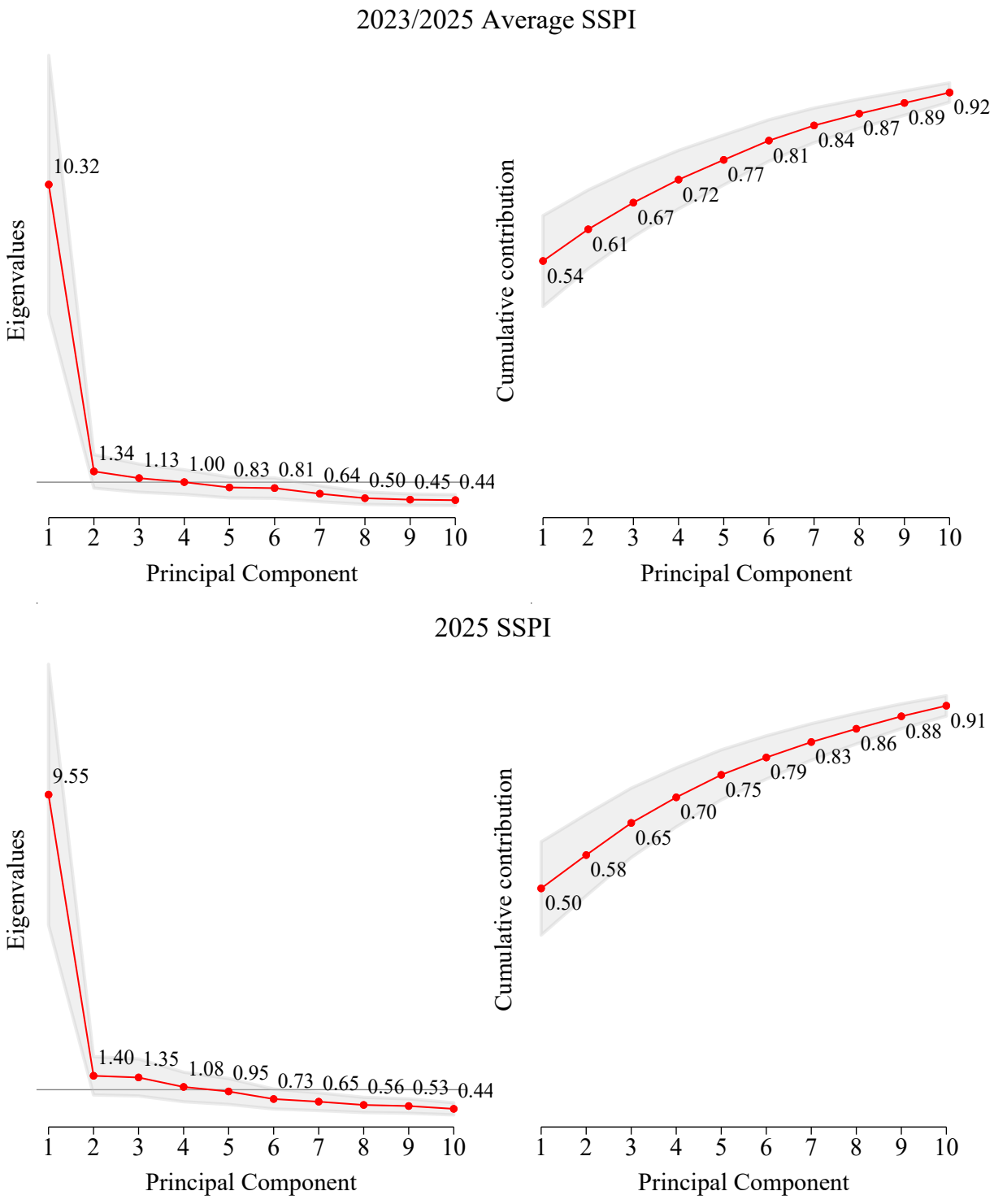


Figure 1. Eigenvalues (left panel) and cumulative contributions (right panel) of estimated PC, based on PCA for all 50 countries based on 2025 SSPI, and 2023/2025 average SSPI[a]

Source: Authors.

Notes: [a] Gray areas indicate corresponding 95% confidence intervals, which are estimated under the assumption that all variables follow joint multivariate normal distribution, and the variance-covariance matrix of the observations has all distinct and strictly positive eigenvalues (Anderson 1963; Jackson 2003).

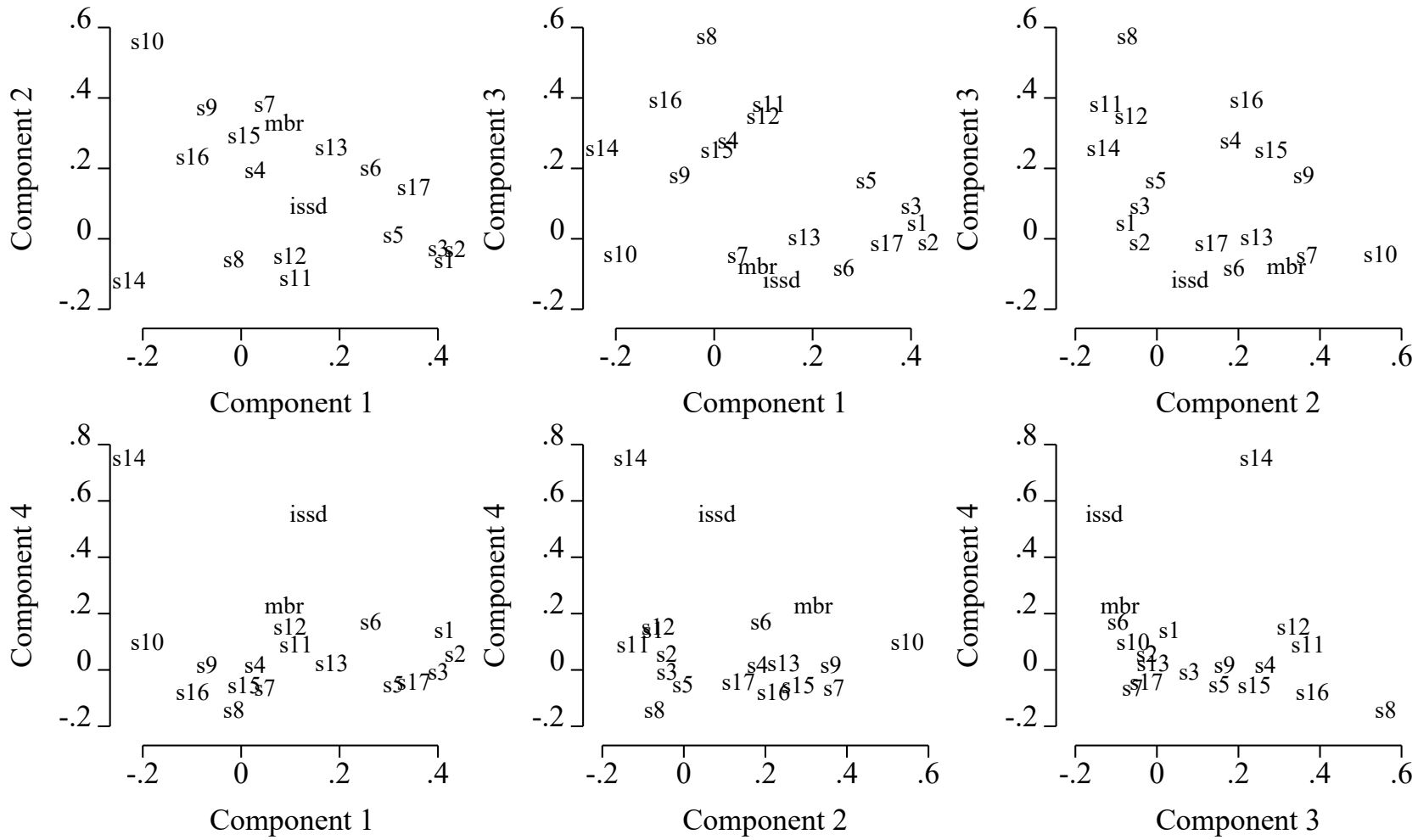


Figure 2. Loadings of variables for the first four principal components based on PCA for all 50 SSPI countries, based on averages of 2023 and 2025 SSPI scores[a]

Source: Authors.

Notes: [a] S1 through S17 in figures indicate the relations of coefficients between each of the first 4 PC for SSPI-1 through SSPI-17, respectively. [b] Figures are based on "rotated" component loadings.

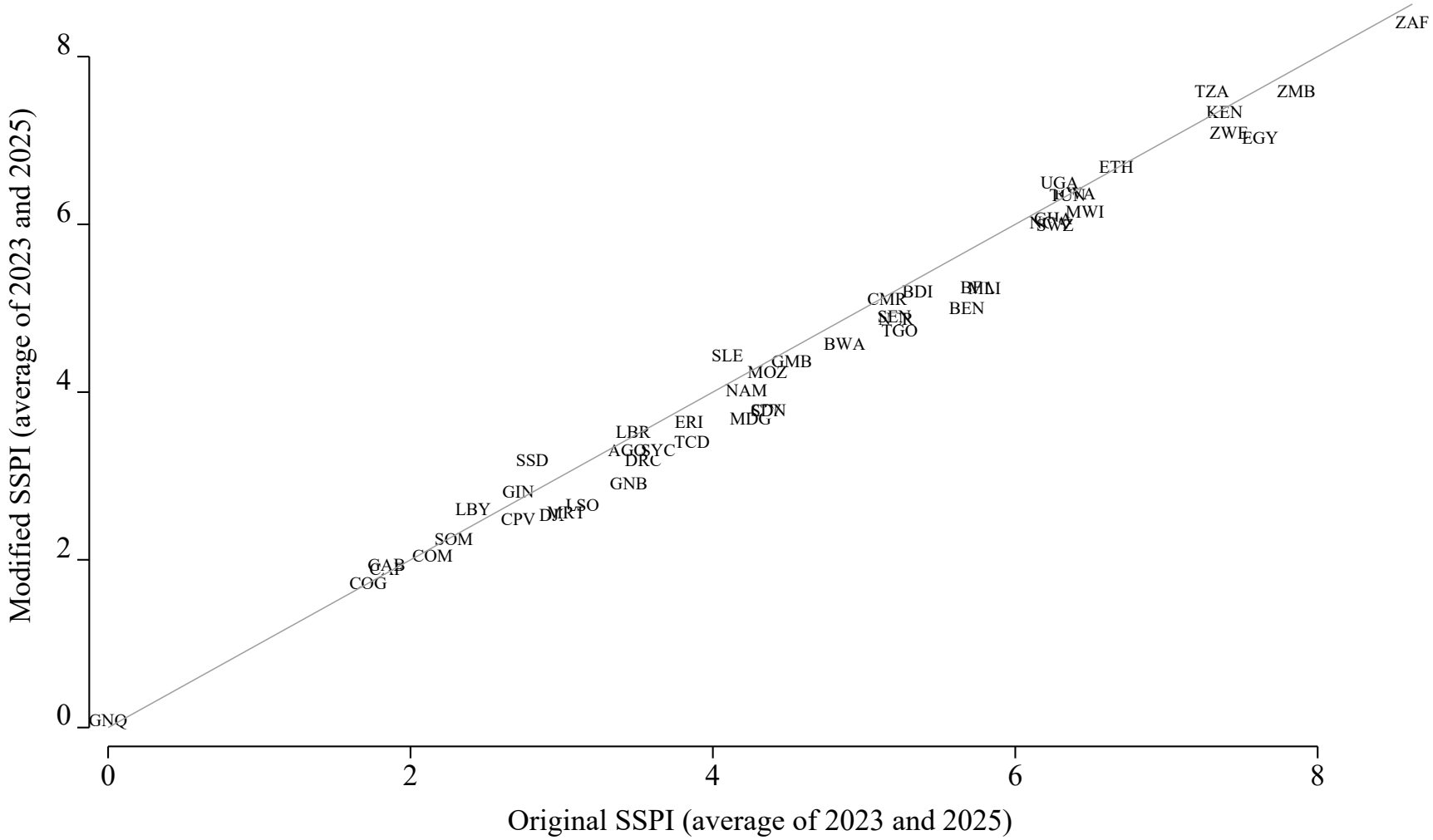


Figure 3. Comparison of modified SSPI score (composite index) with original SSPI score (simple average of 17 SSPIs), based on the averages of 2023 and 2025 SSPI scores

Source: Authors estimation based on PCA and composite-index construction method following Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005).

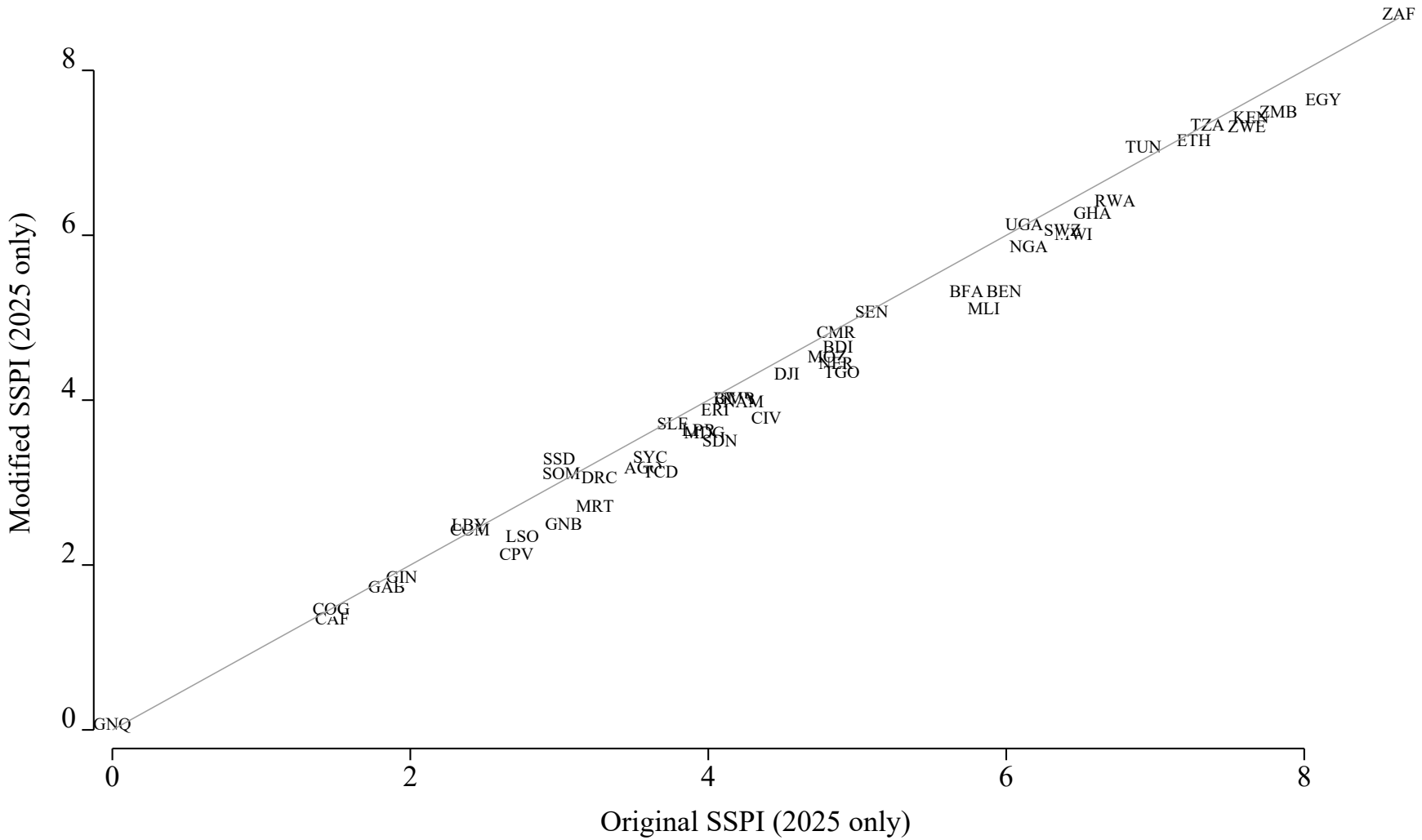


Figure 4. Comparison of modified SSPI score (composite index) with original SSPI score (simple average of 17 SSPIs), based only on 2025 SSPI scores

Source: Authors estimation based on PCA and composite-index construction method following Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005).

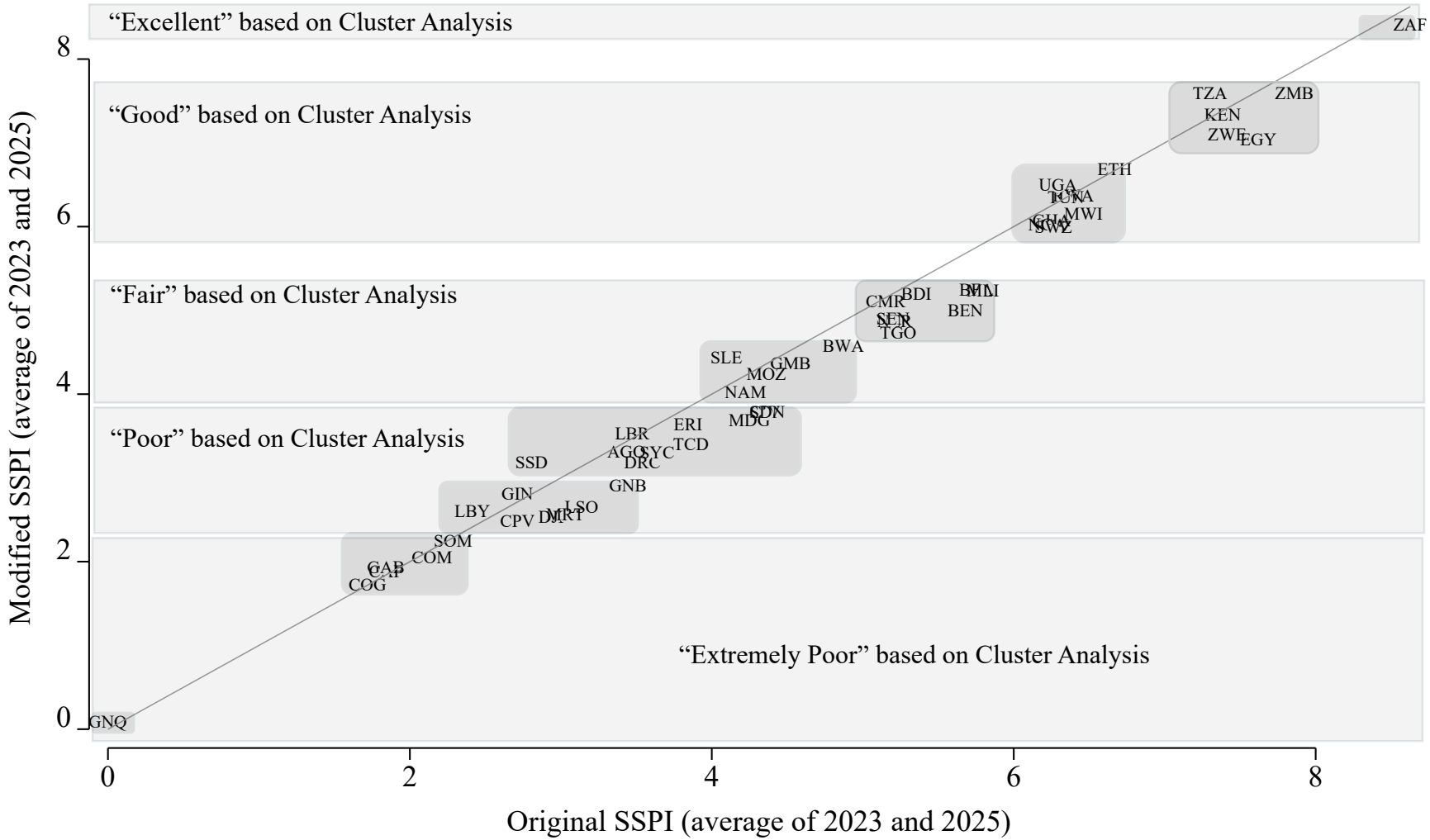


Figure 5. Comparison of modified SSPI score (composite index) with original SSPI score (simple average of 17 SSPIs), based on the averages of 2023 and 2025 SSPI scores

Source: Authors estimation based on PCA and composite-index construction method following Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005).

Appendix

Appendix A1: Computation of modified SSPI scores from multiple principal component scores

Following Berlage and Terweduwe (1988), Nicoletti et al. (2000), and Nardo et al. (2005), the computation of modified SSPI scores are based on the 4 Principal Components (PCs) in 5.1.1.

First, based on the 4 PCs, we obtain rotated PCs, which, as is well known in the PCA literature, provide revised loadings for each of which is more clearly associated with a specific PC (Harman, 1976; Gorsuch, 1983). We employ the rotation method based on Kaiser's (1958) approach, utilizing Kaiser-Horst normalization (Horst, 1965), which is generally considered more desirable than the method without normalization.[12] The rotation leads to the results in Table 6 (based only on 2025 SSPI) and Table 7 (based on the averages of 2023 SSPI and 2025 SSPI), including updated loadings, standardized weights (coefficients) with which each SSPI variable contributes to each PC, and weights (%) with which each PC contributes to the computation of modified SSPI scores (which is based on the variance explained by each PC).

Second, modified PCs are computed using the largest weight for each SSPI variable (shaded cells in Table 6 and Table 7, respectively). For example, in Table 6, for SSPI-1, the weight of .1638 for PC1 is larger than the weights for PC2, PC3 or PC4 (.0042, .0059, and .0062 respectively).

Third, raw modified SSPI scores are computed as a weighted sum of modified PCs, using weights provided at the bottom row.

Lastly, the raw modified SSPI scores are rescaled so that the sum of the weights of variables in the shaded cells multiplied by the weights at the bottom row adds up to 1. Rescaling this way makes the modified SSPI scores comparable to the original SSPI scores.

[12] Importantly, there are numerous other ways to conduct PCA rotation. In our analyses, we also conduct robustness checks across different PCA rotation methods. Results are shown in Table 10 in Appendix.

Table 6. Results of rotated-loadings and related results of PCA (2025 SSPI)

SSPI Variables	PCs from Principal Component Analyses in Figure 2							
	PC 1		PC 2		PC 3		PC4	
	Loadings	Weights in PC	Loadings	Weights in PC	Loadings	Weights in PC	Loadings	Weights in PC
SSPI-1	0.4047	.1638	–0.0649	.0042	0.0766	.0059	0.0785	.0062
SSPI-2	0.4193	.1758	–0.0612	.0037	0.0269	.0007	–0.0122	.0001
SSPI-3	0.3851	.1483	–0.0182	.0003	0.0094	.0001	0.0357	.0013
SSPI-4	0.0621	.0039	0.2482	.0616	0.1412	.0199	0.0253	.0006
SSPI-5	0.3153	.0994	0.0498	.0025	0.0113	.0001	0.0187	.0003
SSPI-6	0.3022	.0913	0.1318	.0174	–0.0796	.0063	0.0424	.0018
SSPI-7	–0.0109	.0001	0.4128	.1704	–0.0949	.0090	–0.1354	.0183
SSPI-8	0.0035	.0000	–0.0062	.0000	0.6295	.3963	–0.2182	.0476
SSPI-9	–0.1457	.0212	0.4345	.1888	0.1573	.0248	0.0502	.0025
SSPI-10	–0.0372	.0014	0.4831	.2334	–0.179	.0320	–0.0286	.0008
SSPI-11	0.1754	.0308	–0.1375	.0189	0.386	.1490	0.1149	.0132
SSPI-12	0.0919	.0085	0.0047	.0000	0.2666	.0711	0.2985	.0891
SSPI-13	0.1168	.0136	0.2755	.0759	0.0022	.0000	0.041	.0017
SSPI-14	–0.1729	.0299	–0.028	.0008	0.0532	.0028	0.7938	.6301
SSPI-15	–0.0209	.0004	0.3052	.0932	0.1746	.0305	0.0616	.0038
SSPI-16	–0.1011	.0102	0.2181	.0476	0.4359	.1900	0.042	.0018
SSPI-17	0.3635	.1322	0.0612	.0037	0.0177	.0003	–0.1187	.0141
ISSD	0.1832	.0336	0.0935	.0087	–0.2097	.0440	0.4076	.1662
Member Status	0.1889	.0357	0.2622	.0688	–0.1308	.0171	0.0201	.0004
Variance explained	4.960		4.464		2.320		1.725	
Weights of PC in summary indicator	.368		.331		.172		.129	

Source: Authors.

Notes: PC = Principal Component. SSPI = Seed Sector Performance Index.

Table 7. Results of rotated-loadings and related results of PCA (2023/2025 average SSPI)

SSPI Variables	PCs from principal component analyses in Figure 2							
	PC 1		PC 2		PC 3		PC4	
	Loadings	Weights in PC	Loadings	Weights in PC	Loadings	Weights in PC	Loadings	Weights in PC
SSPI-1	0.4139	.1713	–0.0747	.0056	0.0312	.0010	0.1258	.0158
SSPI-2	0.4355	.1896	–0.0414	.0017	–0.0242	.0006	0.0405	.0016
SSPI-3	0.4014	.1612	–0.0405	.0016	0.0802	.0064	–0.0213	.0005
SSPI-4	0.0286	.0008	0.1812	.0328	0.2663	.0709	0.0027	.0000
SSPI-5	0.3098	.0960	–0.0019	.0000	0.1536	.0236	–0.0685	.0047
SSPI-6	0.2636	.0695	0.1894	.0359	–0.0951	.0090	0.1543	.0238
SSPI-7	0.0481	.0023	0.3684	.1357	–0.0591	.0035	–0.0791	.0063
SSPI-8	–0.0147	.0002	–0.0716	.0051	0.5616	.3153	–0.1591	.0253
SSPI-9	–0.0696	.0048	0.3606	.1300	0.1665	.0277	0.0023	.0000
SSPI-10	–0.1903	.0362	0.5488	.3012	–0.0579	.0034	0.0835	.0070
SSPI-11	0.1111	.0123	–0.1247	.0156	0.3699	.1368	0.0727	.0053
SSPI-12	0.0999	.0100	–0.0621	.0039	0.336	.1129	0.1362	.0186
SSPI-13	0.1845	.0340	0.2462	.0606	–0.0078	.0001	0.0088	.0001
SSPI-14	–0.2275	.0517	–0.1306	.0170	0.2445	.0598	0.7351	.5403
SSPI-15	0.0067	.0000	0.2813	.0791	0.2399	.0576	–0.0713	.0051
SSPI-16	–0.0986	.0097	0.2206	.0487	0.3822	.1461	–0.0938	.0088
SSPI-17	0.3516	.1236	0.1344	.0181	–0.0253	.0006	–0.0581	.0034
ISSD	0.1372	.0188	0.0811	.0066	–0.1289	.0166	0.5366	.2879
Member Status	0.0878	.0077	0.3175	.1008	–0.0905	.0082	0.2138	.0457
Variance explained	4.590		3.864		3.642		1.661	
Weights of PC in summary indicator	.334		.281		.265		.121	

Source: Authors.

Notes: PC = Principal Component. SSPI = Seed Sector Performance Index.

Appendix A2: Sparse principal component analysis (Sparse PCA)[13]

As is described in Jolliffe et al. (2003) and Hubert et al. (2016), sparse PCA is generally designed to solve the following problems. Starting with a $n \times p$ data matrix $\boldsymbol{X}$ (whereby n is the number of observations and p is the full set of variables originally considered in PCA) and each variable in $\boldsymbol{X}$ is standardized with unit variance.

A standard PCA finds linear combinations (principal components) $\mathbf{a}_k'\boldsymbol{X}$ $(k = 1,2, \dots, p)$, in which $\mathbf{a}_k$ is the vector of coefficients or loadings for the kth PC, such that $\mathbf{a}_k'$ maximizes

$$\begin{gathered} \mathbf{a}_k'\mathbf{R}\alpha_k \\ \text{s.t.} \\ \mathbf{a}_k'\mathbf{a}_k = 1 \text{ and } \mathbf{a}_h'\mathbf{a}_k = 0 \text{ (for } k \geq 2, h < k). \end{gathered} \tag{1}$$

The notation $\mathbf{R}$ is the sample correlation matrix. The first constraint, $\mathbf{a}_k'\mathbf{a}_k = 1$ ensures that the solution is bounded, while the second constraint $\mathbf{a}_h'\mathbf{a}_k = 0$ ensures the orthogonality between each PC.

The idea of sparse-PCA originally developed by Jolliffe et al. (2003) is to solve original PCA (1) by adding penalization term

$$\begin{gathered} \mathbf{a}_k'\mathbf{R}\mathbf{a}_k - \lambda \sum_{j=1}^{p} \left|\mathrm{a}_{kj}\right| \\ \text{s.t.} \\ \mathbf{a}_k'\mathbf{a}_k = 1 \text{ and } \mathbf{a}_h'\mathbf{a}_k = 0 \text{ (for } k \geq 2, h < k). \end{gathered} \tag{2}$$

in which a_{kj} is the jth coefficients of the kth vector $\mathbf{a}_k$, $(k = 1.2, \dots, p)$ and $\lambda(\geq 0)$ is the LASSO penalization parameter. The term $\sum_{j=1}^{p}\left|\mathrm{a}_{kj}\right|$ is the sum of absolute values of all coefficients in $\mathbf{a}_k$. Intuitively, when a vector $\mathbf{a}_k$ has many non-zero coefficients (and thus less sparse), this term becomes larger (and more positive), lowers the value of the objective function. In contrast, if $\mathbf{a}_k$ is sparser (with many coefficients being zero), the term becomes smaller, and thus the solution is more likely to be selected as final. A more positive, larger value of λ corresponds to greater sparsity, while $\lambda = 0$ corresponds to no sparsity.

Hubert et al. (2016) further extends the SPCA method (2) by integrating it into the Robust PCA approach which also addresses the potential outliers (Hubert et al., 2005), developing a so-called Robust-SPCA (ROSPCA). In our paper, we estimate ROSPCA in statistical software `R`, using `rospca` function in the `rospca` package (Reynkens and Todorov 2024).

Selection of λ

While our analyses focus on the sensitivity of results with respect to a range of values for λ, we also highlight λ with certain property. Specifically, an optimal λ can be selected based on the

[13]The description here largely draws on Erichson et al. (2020)

Bayesian Information Criterion (BIC) as described in Hubert et al., (2016), using the `selectLambda` function which too is available in the `rospca` package (Reynkens and Todorov 2024). A key parameter k within the `selectLambda` function is selected using the criterion as described in Hubert et al. (2005, p.66) as suggested in Reynkens and Todorov (2024).

Appendix A3. Imputation of missing observations within the PCA framework

General descriptions of imputation approaches

Following Dray and Josse (2015), the imputation approach by Josse and Husson (2013) used in our study can be described as minimizing

$$\left\| \boldsymbol{W} \circ \left(\boldsymbol{X} - \widehat{\boldsymbol{X}} \right) \right\|^2 \tag{3}$$

in which $\boldsymbol{X}$ is $n \times p$ matrix of original data as described in Appendix A2. The matrix $\widehat{\boldsymbol{X}}$ is the solution of a standard PCA (the best approximation of original matrix $\boldsymbol{X}$ with rank equivalent to the number of PC). $\boldsymbol{W}$ is $n \times p$ matrix consisting of indicators of the missing status of corresponding element in $\boldsymbol{X}$, that is, $w_{np} = 0$ if x_{np} is missing and $w_{np} = 1$ if x_{np} is nonmissing. The symbol $\circ$ denotes the elementwise product. Thus, the problem (3) differs from a standard PCA which simply minimizes $\left\| \mathbf{X} - \widehat{\mathbf{X}} \right\|^2$. Unlike the standard PCA, there is no explicit solution for (3), and thus (3) is solved through the iterative PCA method (Kiers 1997), also known as the expectation–maximization (EM)-PCA algorithm (Josse and Husson 2013; Dray and Josse 2015). Specifically, missing values are first replaced by some random values, PCA is applied on the filled-in data, and missing values are then updated by the fitted values $\widehat{\boldsymbol{X}}$ using a predefined number of PC. The optimal candidate for the predefined number of PC can be selected through the methods described in Josse and Husson (2011). These procedures are repeated until solutions reach a convergence (Dray and Josse, 2015).

Estimation

The imputation is conducted in statistical software `R`, using `imputePCA` function in the `missMDA` package (Josse and Husson 2016). One of the key parameters in `imputePCA`, `ncp` which sets the number of predefined PC used to predict the missing entries, is estimated following Josse and Husson (2011) as described above, and using the function `estim_ncpPCA` in the `missMDA` package.

Shares of missing observations considered in the past approaches

Past studies in the field provide indicative evidence that imputation methods described above may be fairly reliable when the shares of missing observations are no more than 20 percent or so, while the results can become increasingly less reliable as the shares grow. For example, Josse and Husson (2013, section 3.4) demonstrate simulation approaches using the data in which generally 1 ~ 3 out of 12 observations are missing, depending on the variables. Similarly, Dray and Josse (2015) conduct simulations in which the shares of missing-values vary across 10 percent , 20 percent , and 50 percent , in small-sizes data with 20 (as well as 50 and 100) observations, and show that the methods by Josse and Husson (2013) generally work reliably when the shares of missing values are 10 percent or 20 percent . Dray and Josse (2015) also demonstrate additional examples using a past study in which about 50 percent of observations are missing.

Appendix A4: Multiple-Correspondence Analysis

The results in Table 8 suggest that 1 dimension, 3 primary dimensions, and 1 primary dimension explain close to 80% of overall dispersions (also called inertia in MCA literature, which is roughly equivalent to overall variation in PCA), respectively. Based on these results, we use the 1st predicted coordinate, 1st through 3rd predicted coordinates, and 1st predicted coordinate as inputs into PCA, for ISSD-related, EBA-related, and Membership-related variables, respectively. Appendix Figure 6 illustrates the 3 MCA-predicted scores of EBA variables, showing how 9 EBA-related binary variables are approximated by these 3-dimension scores.

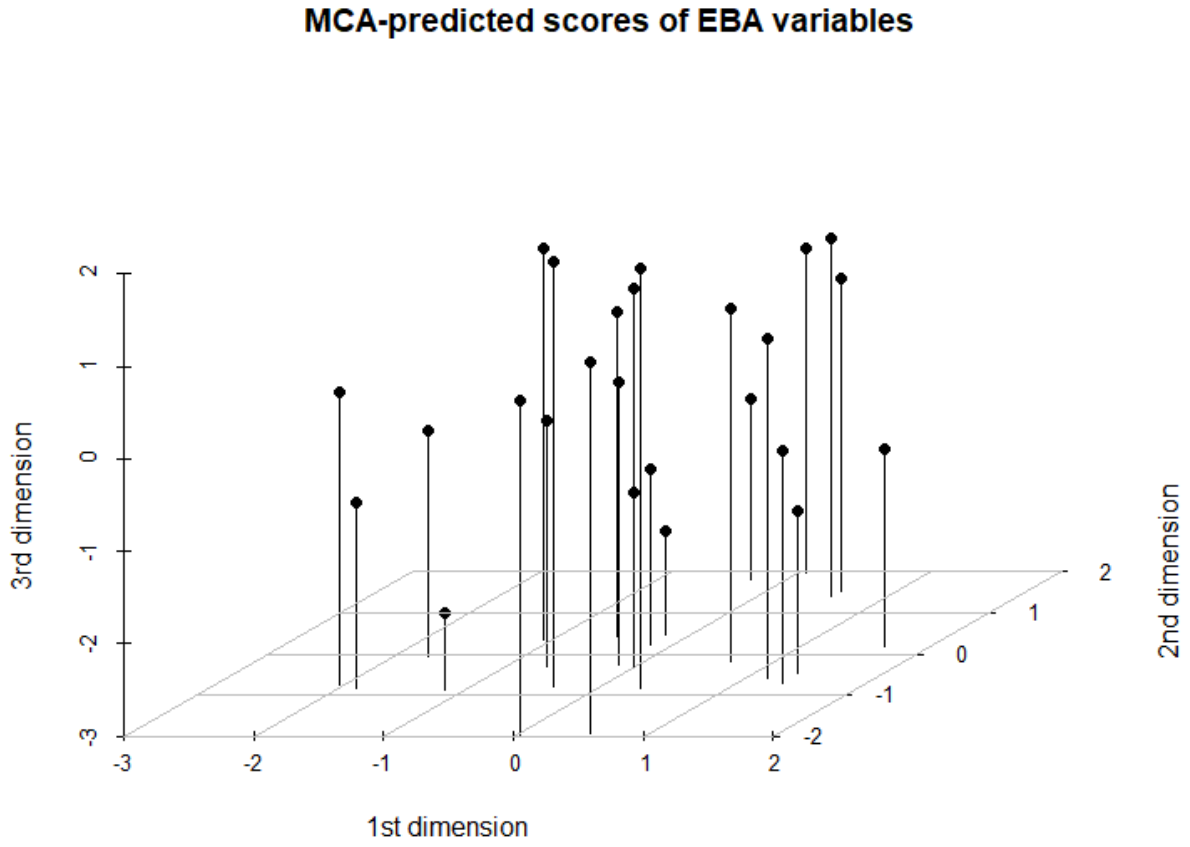
Table 8. Cumulative contributions (%) of each dimension to overall dispersions (inertia) among each set of variables based on multiple correspondence analyses (MCA)

Dimensions	ISSD variables (3 variables)[a]	EBA variables (9 variables)[b]	Membership variables (5 variables)[c]
Dimension 1	**85.69**	**56.61**	**68.05**
Dimension 2	97.81	**73.80**	**83.52**
Dimension 3	100.00	**88.57**	94.60
Dimension 4	–	93.25	99.48
Dimension 5	–	96.60	100.00
Dimension 6	–	98.34	–
Dimension 7	–	99.34	–
Dimension 8	–	99.84	–
Dimension 9	–	100.00	–
No. of observations	50	30	50

Source: Authors.

Notes: ISSD = The integrated seed sector development; EBA = Enabling the Business of Agriculture. [a] These variables refer to 3 ISSD variables, 9 EBA variables, and 5 membership variables (ITPGRFA, Nagoya, UPOV, OECD, ISTA) in Table 2.

Figure 6. Standardized MCA-predicted scores of EBA variables (3 dimensions)



Source: Authors' estimations based on Multiple Correspondence Analysis.
Note: Each dot represents a country.

Appendix A5: Supplementary results

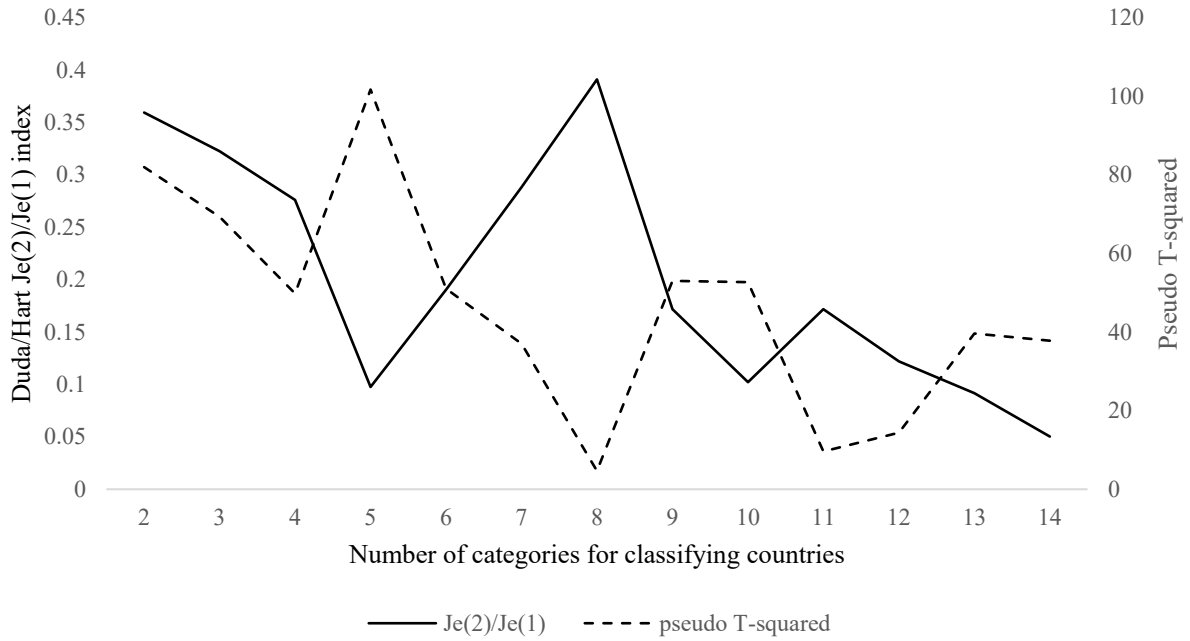
Table 9. Modified SSPI categories of 47 countries (2023 SSPI only)[a]

Country	Based on 2023 SSPI only	
	(a) Original SSPI scores	(d) Modified SSPI scores[b]
South Africa	8.62	8.27
Zambia	7.89	8.03
Tanzania	7.25	7.56
Zimbabwe	7.21	7.29
Kenya	7.13	7.19
Egypt	7.11	6.52
Malawi	6.47	6.15
Uganda	6.47	6.52
Nigeria	6.29	6.17
Eswatini	6.15	6.19
Ethiopia	6.08	5.81
Rwanda	6.05	5.97
Ghana	5.93	6.08
Burundi	5.78	5.68
Burkina Faso	5.77	5.09
Tunisia	5.77	5.64
Mali	5.74	5.19
Togo	5.58	4.95
Niger	5.57	5.24
Botswana	5.56	5.09
Cameroon	5.45	5.20
Benin	5.37	4.58
Senegal	5.31	5.25
Gambia	4.87	4.42
Sudan	4.66	4.00
Madagascar	4.52	3.99
Sierra-Leone	4.43	4.55
Côte d'Ivoire	4.32	3.48
Namibia	4.21	3.82
Guinea-Bissau	4.10	3.57
Chad	4.04	3.27
Mozambique	3.93	3.80
Seychelles	3.90	3.55
DRC	3.81	3.22
Eritrea	3.64	3.28
Lesotho	3.52	2.98
Guinea	3.48	3.36
Angola	3.31	3.00
Liberia	3.20	3.08
Mauritania	2.82	2.77
Libya	2.76	2.12
South Sudan	2.61	3.11
Central African Rep.	2.21	2.00
Comoros	2.14	1.66
Congo, Rep. of	1.97	1.48
Somalia	1.56	1.29
Djibouti	1.35	1.27

Source: AUC et al. (2024) for Overall SSPI scores; Other figures are based on authors' analyses.

Notes: [a] Coloring of quintiles for cluster-analyses derived results: Green = 1st, Light green = 2nd, Yellow = 3rd, Orange = 4th, Red = 5th, which correspond to "Excellent". "Good", "Fair", "Poor" and "Extremely Poor" in AUC et al. (2024).[b] Cluster analyses are based on hierarchical cluster analyses with *average* linkage method with similarity measures based on Euclidean distance, which is suggested to work well for many situations and is reasonably robust (Kaufman and Rousseeuw 1990).

Figure 7. Suitability of different number of categories to classify countries through modified SSPI scores[a]



Source: Authors.
Notes: [a] Results are based on Hierarchical cluster analyses with average linkage applied to modified SSPI scores in Figure 3. [b] A higher value of Je(2)/Je(1) and a lower value of Pseudo T-squared indicate more distinctive clustering (Duda and Hart, 1973).

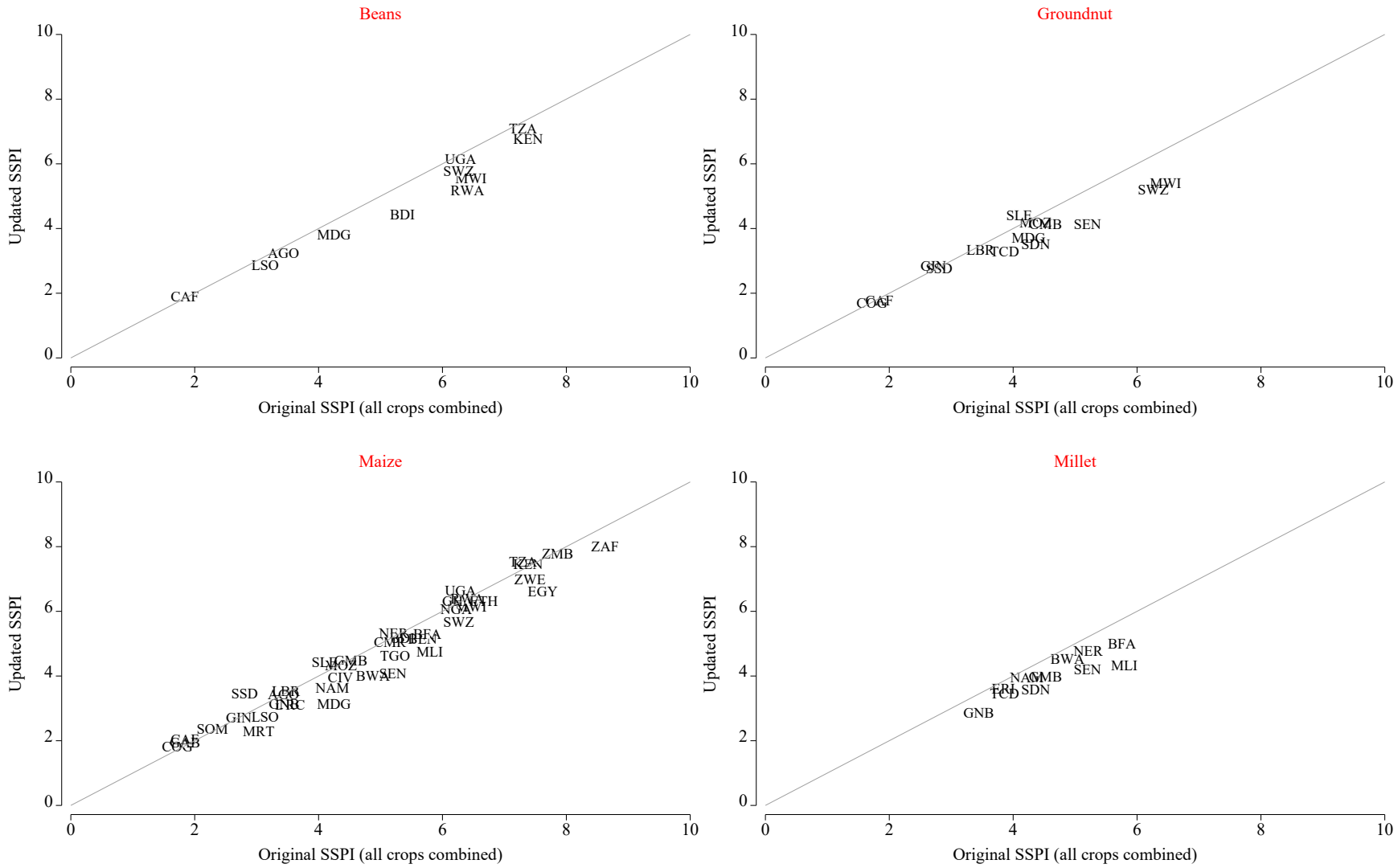
Table 10. Robustness of the differences from the original overall SSPI scores across different PCA rotation methods[a]

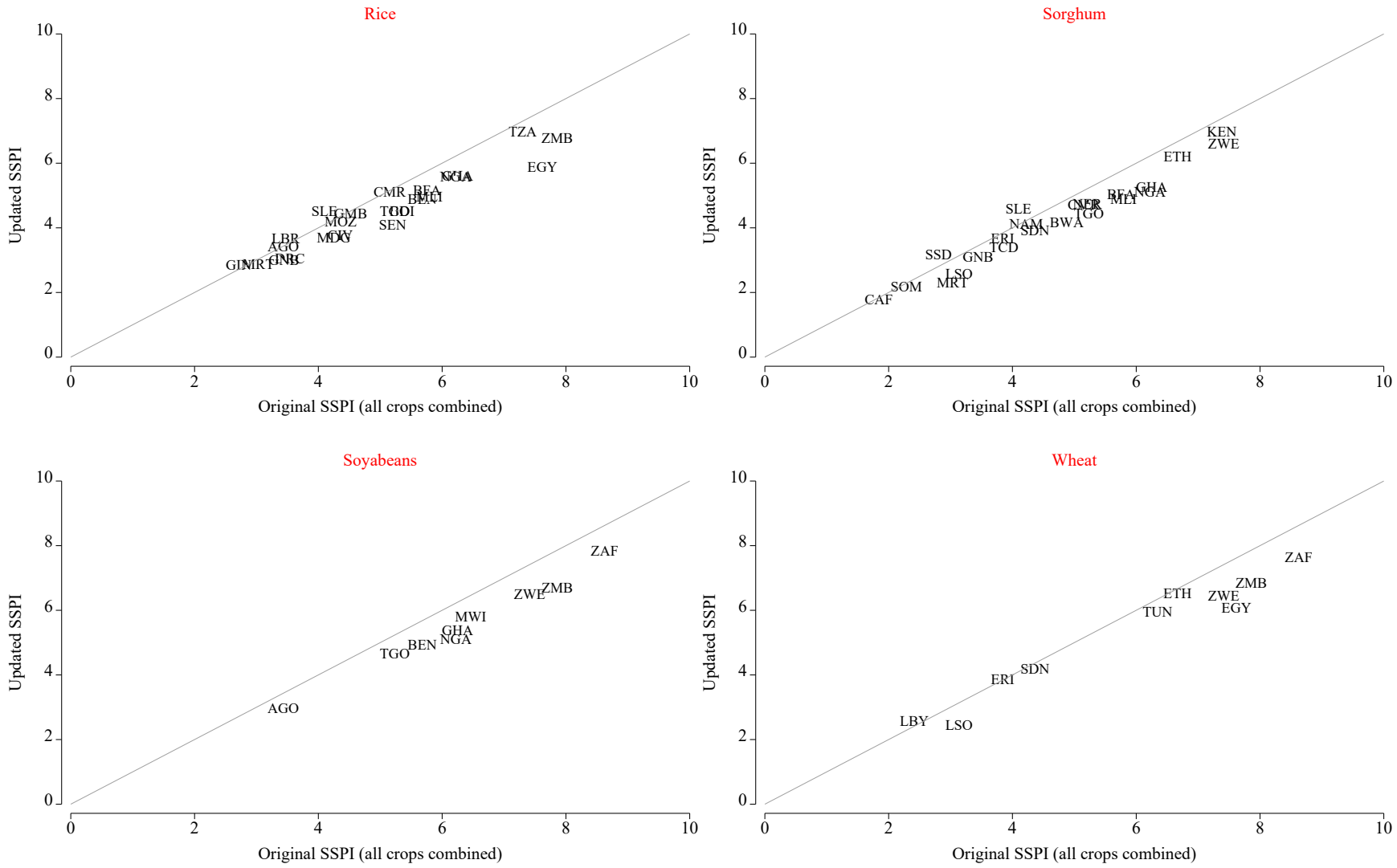
	PCA rotation methods used							
Country	Varimax (default results) (Kaiser 1958)	Vgpf (Kaiser 1958)	Quartimax (Harman 1976)	Parsimax (Crawford & Ferguson 1970)	Minimum entropy (Jennrich 2004)	Tandem criterion 1 (Cormey 1967)	Tandem criterion 2 (Cormey 1967)	Oblique (Jennrich 1979)
Angola	–0.54	–0.54	–0.55	–0.52	–0.60	–0.59	–0.49	–0.55
Burundi	–0.32	–0.32	–0.27	–0.42	–0.32	–0.36	–0.42	–0.33
Benin	–0.94	–0.94	–0.92	–0.97	–1.00	–0.97	–0.94	–1.03
Burkina Faso	–0.47	–0.47	–0.45	–0.46	–0.50	–0.47	–0.45	–0.52
Botswana	–0.22	–0.22	–0.27	–0.19	–0.27	–0.47	–0.18	–0.19
Central Africa	–0.27	–0.27	–0.31	–0.23	–0.29	–0.33	–0.22	–0.28
Côte d'Ivoire	–0.98	–0.98	–1.02	–0.95	–1.00	–1.03	–0.94	–1.04
Cameroon	–0.06	–0.06	–0.14	0.07	–0.08	–0.19	0.09	–0.05
Congo, Rep. of	–0.44	–0.44	–0.47	–0.40	–0.47	–0.44	–0.39	–0.47
Comoros	–0.41	–0.41	–0.43	–0.38	–0.43	–0.45	–0.36	–0.43
Cape Verde	–0.38	–0.38	–0.41	–0.33	–0.43	–0.38	–0.31	–0.41
Djibouti	–0.11	–0.11	–0.20	–0.07	–0.14	–0.35	–0.05	–0.09
DRC	–0.70	–0.70	–0.72	–0.68	–0.71	–0.68	–0.68	–0.75
Egypt	–1.32	–1.32	–1.29	–1.36	–1.37	–0.90	–1.33	–1.48
Eritrea	–0.36	–0.36	–0.32	–0.38	–0.42	–0.35	–0.35	–0.40
Ethiopia	–0.73	–0.73	–0.65	–0.71	–0.75	–0.67	–0.68	–0.80
Ghana	–0.28	–0.28	–0.17	–0.40	–0.31	–0.23	–0.38	–0.33
Guinea	–0.41	–0.41	–0.40	–0.36	–0.44	–0.40	–0.34	–0.43
Gambia	–0.51	–0.51	–0.47	–0.54	–0.58	–0.44	–0.49	–0.55
Guinea–Bissau	–0.44	–0.44	–0.35	–0.54	–0.50	–0.39	–0.53	–0.47
Equatorial Guinea	0.03	0.03	0.02	0.05	0.03	0.06	0.04	0.03
Kenya	–0.35	–0.35	–0.41	–0.29	–0.33	–0.27	–0.31	–0.40
Liberia	–0.30	–0.30	–0.35	–0.15	–0.34	–0.47	–0.13	–0.30
Libya	–0.48	–0.48	–0.38	–0.62	–0.49	–0.34	–0.62	–0.55
Lesotho	–0.31	–0.31	–0.35	–0.27	–0.37	–0.43	–0.24	–0.31
Madagascar	–0.86	–0.86	–0.85	–0.83	–0.86	–0.76	–0.82	–0.93
Mali	–1.14	–1.14	–1.10	–1.15	–1.15	–0.95	–1.13	–1.25
Mozambique	–0.39	–0.39	–0.42	–0.30	–0.41	–0.52	–0.29	–0.40
Mauritania	–0.58	–0.58	–0.50	–0.68	–0.61	–0.45	–0.67	–0.63
Malawi	–0.58	–0.58	–0.53	–0.59	–0.60	–0.55	–0.57	–0.64
Namibia	–0.02	–0.02	–0.18	0.04	–0.02	–0.56	0.01	0.05
Niger	–0.64	–0.64	–0.62	–0.61	–0.65	–0.72	–0.59	–0.67
Nigeria	–0.20	–0.20	–0.26	–0.06	–0.21	–0.20	–0.05	–0.22
Rwanda	–0.37	–0.37	–0.33	–0.45	–0.36	–0.53	–0.44	–0.36
Sudan	–0.81	–0.81	–0.78	–0.85	–0.85	–0.83	–0.84	–0.88
Senegal	–0.78	–0.78	–0.77	–0.71	–0.79	–0.44	–0.70	–0.88
Sierra–Leone	–0.13	–0.13	–0.06	–0.09	–0.17	–0.14	–0.05	–0.13
Somalia	–0.07	–0.07	–0.03	–0.14	–0.09	–0.06	–0.12	–0.07
South Sudan	0.43	0.43	0.53	0.40	0.44	0.42	0.41	0.47
Eswatini	–0.25	–0.25	–0.21	–0.25	–0.28	–0.35	–0.22	–0.27
Seychelles	–0.19	–0.19	–0.30	–0.05	–0.26	–0.40	0.00	–0.18
Chad	–0.62	–0.62	–0.64	–0.59	–0.68	–0.70	–0.56	–0.66
Togo	–0.71	–0.71	–0.64	–0.81	–0.76	–0.71	–0.78	–0.76
Tunisia	–0.78	–0.78	–0.70	–0.77	–0.81	–0.54	–0.73	–0.89
Tanzania	0.36	0.36	0.25	0.53	0.37	0.21	0.53	0.41
Uganda	–0.03	–0.03	–0.06	0.10	–0.05	–0.06	0.12	–0.04
South Africa	–1.08	–1.08	–1.01	–1.08	–1.11	–0.63	–1.06	–1.25
Zambia	–0.62	–0.62	–0.55	–0.59	–0.65	–0.35	–0.56	–0.71
Zimbabwe	–0.56	–0.56	–0.47	–0.55	–0.58	–0.30	–0.53	–0.65

Source: Authors.

Notes: [a] Darker colors imply more negative values.

Figure 8. Crop-specific SSPI (original SSPI and updated SSPI)





Source: Authors.

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