We present the output data of Robust Principal Component Analysis (RPCA) applied to global crop yield variability of maize, rice, sorghum and soybean (MRSS) as presented in the publication “Climate drives variability and joint variability of global crop yields” (Naja et al., 2019). Global maps of the correlation between all the principal components (PCs) acquired from the low rank matrix (L) of MRSS and Palmer Drought Severity Index (PDSI), air temperature anomalies (ATa) and sea surface temperature anomalies (SSTa) are provided in this article. We present co-varying countries, impacted cropland areas across global countries, and 10 global regions by climate and the association between PCs and multiple atmospheric and oceanic indices. Moreover, the joint dependency between PCs of MRSS yields are presented using two different approaches.

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Concurrent and one year-lag correlation between all the PCs of maize, rice, sorghum and soybean (MRSS) acquired from the low rank matrix (L) of Robust Principal Component Analysis (RPCA) and annual average of PDSI, air temperature anomalies (ATa) and sea surface temperature anomalies (SSTa) (in total 412 maps) are provided in the supplementary. In all the maps, significant correlations (95% confidence) over croplands of MRSS are marked with small black dots. The first few PCs explain a large portion of the crop yield variability, and succeeding PCs account for the remaining variability. The variability explained by each PC is shown at the top of each map. The boundary of the countries with large loading values are highlighted in orange (large positive loading values) and blue (large negative loadings values). These countries co-vary similarly/oppositely (same loading sign value countries co-vary similarly and vice versa), and they explain the variance of that PC the most.

Nine tables in the Microsoft Excel Worksheets are included in the supplementary. MRSS producer countries with complete yield dataset from 1961 to 2013 that are used as input for RPCA are presented in Table S1. These countries are categorized in 10 global regions. Table S2 exhibits countries with large positive and negative loading values (co-varying countries). The studied countries are ranked based on MRSS production, export and import in 2013 (Table S3). The area (in hectares) of MRSS croplands in global countries (10 major MRSS producers) that experienced the influence of concurrent and one-year lag of ATa and PDSI are presented in Table S4 (Table S5). In Table S4 and S5 we computed the cropland...
areas that are impacted by AT or PDSI, in either concurrent or lag phase too (we call it the regions that
are impacted by local climate, see Fig. 1). The percentage of the impacted croplands by ATa and PDSI
concurrent and lag phases in 10 global regions are exhibited in Table S6. Tables S4, S5 and S6 are based
on PC1 to PC3 of the global maps provided in the supplementary. Table S7 demonstrates the concurrent
and lag correlation between multiple annual average and seasonal average (December, January,
February-DJF) of multiple oceanic and atmospheric indices and PC1 to PC3. Joint dependencies be-
tween PC1 to PC3 is presented in Table S8. Table S9, is similar to Table S8, with the difference that PCs
are computed based on the low rank matrix of crop yields of 17 countries with complete yield data of all
the four crops after 1961.

2. Experimental design, materials, and methods

RPCA [4] was applied on detrended crop yields of MRSS. Country based annual crop yield data
of these crops from 1961 to 2013 are collected from the Food and Agriculture Organization of the
United Nations statistical databases [5]. However, the detrending approach that is used here [6]
leads to losing the first and last three years, but each anomaly value captures the information of
a 7-year window time span and the final time span is from 1964 to 2010. Yield values of some
countries are common in few consecutive years, so this detrending approach leads to undefined
values if there are 7 such years with the same consecutive numbers. The same crop yield values
over a few years may indicate dataset inaccuracy, hence, in order to improve data reliability these
countries are not considered. The final dataset contains 130, 98, 73 and 37 MRSS producer
countries (Table S1). Low rank matrix (L) acquired from RPCA is implemented to compute loadings,
eigenvalues and scores. Loadings contain uncorrelated PCs [7]. Eigenvalues provide a measure of
the variance explained by each PC. RPCA decomposed the L matrix of MRSS into 28, 28, 27 and 20
PCs respectively. Each PC is associated with a score vector. Scores are used to find links between
PCs and climatic data set (PDSI, ATa, SSTa, oceanic and atmospheric indices [8]) by means of
spearman correlation analysis. In order to obtain the global spatial coverage of MRSS croplands, we
combined the irrigated and rain fed maps for each crop [9,10]. The resulting maps are used to
specify the spatial coverage of croplands as well as croplands area (in hectares). We choose co-
varying countries (countries with large positive or negative loading values) based on one stan-
dard deviation exceedance of loadings values from the mean from both sides in each PC. RPCA
applied to global crop yields of MRSS in Argentina, Australia, Brazil, China, Colombia, DR Congo,
India, Italy, Mexico, North Korea, Pakistan, Peru, Romania, South Korea, Tanzania, USA and
Zimbabwe. These countries produce MRSS and they have complete yield data set from 1961 to
2013. The acquired L matrix is used to compute PCs and identify joint variability between crops
(Table S9).

Fig. 1. Schematic illustration of overlapping the significant local climate variability over croplands.
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Transparency document

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dib.2019.103745.

References

[1] E. Najafi, I. Pal, R. Khanbilvardi, Climate drives variability and joint variability of global crop yields, Sci. Total Environ. 662 (2019) 361–372. https://doi.org/10.1016/j.scitotenv.2019.01.172.
[2] E. Najafi, N. Devineni, R.M. Khanbilvardi, F. Kogan, Understanding the Changes in Global Crop Yields through Changes in Climate and Technology, Earth’s Futur., 2018.
[3] E. Najafi, I. Pal, R. Khanbilvardi, Diagnosing extreme drought characteristics across the globe, Sci. Technol. Infus. Clim. Bull. NOAA Annu. Clim. Diagnostics Predict. Work. (2018).
[4] E.J. Candès, X. Li, Y. Ma, J. Wright, Robust principal component analysis? J. Assoc. Comput. Mach vol. 58 (3) (2009).
[5] http://www.fao.org/faostat/en/#data.” FAO, 2016.
[6] T.J. Troy, C. Kipgen, I. Pal, The impact of climate extremes and irrigation on US crop yields, Environ. Res. Lett. 10 (5) (2015), 054013.
[7] I.T. Jolliffe, Principal component analysis, second ed, Encycl. Stat. Behav. Sci. vol. 30 (3) (2002) 487.
[8] http://www.esrl.noaa.gov/psd/.” 2017.
[9] Spatial data access tool (SDAT), ORNL Distributed Active Archive Center, 2017.
[10] F.T. Portmann, S. Siebert, P. Doll, MIRCA2000—global monthly irrigated and rainfed crop areas around the year 2000: a new high-resolution data set for agricultural and hydrological modeling, Glob. Biogeochem. Cycles 24 (2010) 1–24.
[11] E. Najafi, N. Devineni, R. Khanbilvardi, F. Kogan, Global crop yields, climatic trends and technology enhancement, in: American Geophysical Union Fall Meeting 2016, San Francisco, CA, USA, 12–16 December 2016, AGU, Washington, DC, USA, 2016. Abstract #H32C-07.