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ABSTRACT

Due to its biological nature, crop yield carries some natural variability. However, a high yield variability leads to unstable farmer income and may increase the vulnerability of the rural population in low income countries. As a side effect, in some regions this uncertainty contributes to poverty, fight and health diseases. Addressing the issue of yield variability is the basis to reach some of the Sustainable Development Goals (SDGs) stated by the international community in 2015 and aiming at fighting poverty, inequality and tackling climate change. Using national data from the FAO database for 224 countries and 141 crops, we perform a worldwide comparison of crop yield variability to provide an analytical insight on which geographical areas and which crops are more yield unstable. The single country-crop yield series are first de-trended using a robust MM estimator to prevent from the influence of the outlying observations to affect the trend estimates. Then a summary measure of yield variability on the de-trended data is computed for each series. Results are analyzed by Analysis of Variances (ANOVA) for geographical country aggregates, crop aggregates and time periods. Middle East, North Africa and Sub-Saharan Africa appear to be the geographical areas with the highest yield variability, which has increased by around 20% in the last decade.. Results indicate the need for the international community to urgently intervene in these areas to address the issue of yield variability and moving towards the SDGs.

Keywords: crop yield variability, MM robust estimation

JEL code: C13, Q10

1. INTRODUCTION

In 2015 the international community set the Sustainable Development Goals (SDGs), 17 goals aiming at end poverty, fight inequality and tackle climate change by a joint effort of governments, producers and civil society. Promoting food security is the basis to achieve many of these goals and one goal is specifically addressed to pursue it. According to the FAO figures, the world population is expected to increase to almost 10 billions by 2050 and agriculture production needs to keep the pace of this growth (FAO, 2017). Over the last 20 years, the amount of farmland at the world level has stabilized at around 4.9 billion hectares and a future expansion is neither feasible nor desirable. Attention must be paid to promote a sustainable increase in yields and practices targeted to mitigate yield variability. IPCC (2007) highlights that the increased frequency and severity of extreme climate events will have negative consequences on food production and security at the world level by increasing inter-annual crop yield variability. High crop yield variability implies negative consequences to farmers and to the whole population. Indeed, farmers operating in countries where yield are highly variable must deal with highly unstable income and they can hardly plan farm investment. Moreover, population in such countries are v,ulnerable and food insecure and this often results in poverty, fights and health diseases (FAO, 2017). Government interventions are required in countries affected by high yield uncertainty in order to stabilize farmers' income, to protect local population from food shortage and to cooperate to reach the SDGs.

While technical research should develop technologies specifically targeted to reduce the negative consequences of extreme weather events on farmers and local population, statistical-economic research should shed light on yield trend and yield variability and on their drivers. Many studies underline the relationship between yield variability and climate change (Ray et al., 2015; Lobell, 2011) performing worldwide analysis. In particular, Ray et al. (2015) studied the role of climate variation in explaining yield uncertainty of corn, rice, wheat and soybean by analyzing 13,500 political units. They found that one third of yield variability is due to climate variation. Analysing crop yield variability means assessing the part of crop yield that cannot be predicted beforehand. Indeed, crop yield can be decomposed into a trend component and a random component. While the trend component is predictable and is due to technological progress and input use, the random component is the part of yield that cannot be forecasted. Given its unpredictable character, the random component represents the risky component of yield and it is determined by weather, insects, diseases and other factors. This random component is responsible for unstable farmer income and food insecurity. Performing a worldwide analysis on the yield variability allows to compare countries and larger geographical areas in terms of yield risk and gives an analytical indication to international organisations on where to more urgently focus the attention and the efforts towards SDGs.

2. Yield Trend Estimation Issue

Assessing the risky part of yield requires a proper estimation of the trend, as its measure is somehow based on the difference between the observed yield and the expected yield from the trend estimates. The aforementioned studies on the relationship between climate variation and yield variation are focused mainly on the random component of yield and do not pay attention to the issue posed by a proper estimation of the yield trend. Noteworthy, a proper trend estimation is required for an unbiased estimation of the random component of yield. Approaches to estimate the yield trend include deterministic models (Swinton and

King, 1991; Just and Weninger, 1999; Finger 2010 and 2013) and stochastic models (Goodwin and Ker, 1998). Several studies (Claassen and Just, 2011; Sherrick et al., 2004; Harri et al., 2009) found that serial correlation is not a serious issue in yield de-trending, thus supporting the use of deterministic models. Literature on the estimation of deterministic trend does not use comprehensive economic models, since crop yields are simply regressed against a time polynomial. Along the line of Enders (1995), Just and Weninger (1999) proposed to represent the deterministic component of crop yield by a polynomial specification of time whose degree is selected according to the data. Although such a specification lacks an economic causal framework, it is flexible enough to approximate the effects of the economic variables that vary with a low frequency.

One important issue in the estimation of yield trend is the presence of outliers that contaminate the yield series. According to Hawkins (1980, page 1) an outlier is “an observation that deviates so much from other observations as to arouse suspicious that it was generated by a different mechanism”. The presence of one or more outliers in the series can bias the coefficient estimates. In particular, while the intercept will be affected by outliers in the middle of the series, outliers at the beginning or at the end of the series influence the slope coefficient(s). An estimator that is not robust to the presence of outliers is likely to lead to a biased trend estimates when the series is outlier contaminated and, as a consequence, to a biased yield variability[1] estimates. Indeed, if a very good growing season in a year results into exceptionally high yield in that year, the non-robust estimator results in a biased shift of the yield trend upward. Conversely, if a very bad growing season results into exceptionally low yield, the non-robust estimator leads to a biased

[1] Hereafter, the terms yield variability, yield risk, yield uncertainty and random component of yield are used interchangeably.

shift of the yield trend downward. As the yield trend should reflect the average tendency over the years it should be insensitive to the exceptional value recorded in one or a few years. If the trend estimation is not insensitive to that, the computation of the random component of yield based on that outlier-sensitive trend results in biased values.

The application of robust regression techniques overcomes the problem of biased parameter estimates in crop yield detrending when the yield series is outlier-contaminated. A robust estimator is an estimator that has a high breakdown point. The breakdown point represents the smallest fraction of observations that may cause an estimator to take on arbitrarily large aberrant values (Ruckstuhl, 1997). An OLS estimator has a breakdown point of zero as one observation is enough to lead the OLS estimator to take arbitrarily values between $-\infty$ and $+\infty$. Among the class of robust estimators, the MM estimator (Yohai, 1987) is an efficient and robust estimator with a breakdown point of 0.5. It means that if the outlier observations in the series are less than 50% the MM estimator is still unbiased. Due to the dependence on weather events and on other natural events (e.g. pest and diseases), yield series are likely to be contaminated by outliers and thus the use of robust techniques is recommended in the de-trending exercise.

In this paper, we use the large worldwide database on crop yield data of the Food and Agricultural Organisation (FAO) of the United Nations to estimate crop yield variability at country and crop level. The FAO database on yields is a comprehensive database where crop yield data are registered annually at country level since 1961. Despite the weaknesses of dealing with national aggregate data, this dataset represents a powerful source of information for countries where farm level yield data are not publicly available and it is the only source of data to make worldwide comparison of yield data variability across countries for a very large number of crops.

For each country-crop combination, we estimated a deterministic time polynomial models for crop yields by means of a robust regression technique, the MM estimation, which is still barely used in agricultural economics (Harri et al., 2009 and 2011). As yield series are likely to be affected by outliers, e.g. due to exceptional weather conditions, the MM estimator allows to get parameter estimates for yield trend that are not contaminated by outliers and thus it allows an unbiased estimation of yield variability independent of the series being outliers contaminated or not. Finger (2010, 2013) performs Monte Carlo simulations in a crop yield detrending exercise to compare the performance of the MM estimator with two other estimators (OLS and Theil Sen estimator). He founds that MM estimator performs similarly to OLS estimator in case of outliers free series and it outperforms the other two estimators when the series is contaminated by outliers.

The deterministic model was estimated for each single country-crop combination and the data series were de-trended based on the parameter estimates. The de-trended yield data were then used to obtain a measure of yield risk in each country-crop combination. Additionally, analysis of variance (ANOVA) was performed to assess the heterogeneity of yield variability across country aggregates and crop aggregates as well as over time. Finally, the same analysis was performed separately on each of the seven most grown crops at the world level (wheat, corn, rice, soybeans, barley, sorghum, millet).

Besides the need to apply a robust regression technique, another important issue when estimating crop yield variability is the availability of data. Farm level yields are often available as short time series, while some countries, such as many small developing countries, lack any publicly available data on farm level yields. Not surprisingly, most of the available yield trend studies focused on the US, where long series of crop yield data at farm and county level are available. If one wants to perform a worldwide study on crop yield variability, the use of regional/national data is necessary in many cases. However, the use of aggregate data is likely to underestimate the actual farm level yield variability (Claassen and Just, 2011).

Despite this drawback, the use of regional or national level data to estimate yield variability is an important source of information. Indeed, this measure allows a comparison of yield uncertainty across crops and across countries. If crop yield variability is heterogenous across macro-regional areas, the attention of the international community should be addressed to the most uncertain areas in order to promote mitigation strategy and to reduce the farmer's and population vulnerability to the yield variability. The comparison may also be useful for insurance companies to have a rough idea of the level of agricultural production risk in a region when farm level data are not available. In absence of disaggregated data, the use of regional or national data is also the only option available to estimate the variance-covariance matrix of yields in regional or national programming model as well as of partial and general equilibrium model.

3. METHODOLOGY

3.1 Yield trend estimation: MM estimator

The first step in the estimation of country level crop yield variability consists in detrending the time series of crop yield. Following Enders (1995) and Just and Weninger (1999), we modelled the yield series, y_{cit}, for each country c and crop i as a polynomial of time whose degree is selected during the estimation process:

$$y_{cit} = \beta_0 + \beta_1 t + \beta_2 t^2 + e_{cit}$$

where t indicates the time variable[2] and e is the residual. If the quadratic trend parameter estimate (β_2) was statistically significant we concluded that the polynomial degree of that country-crop yield series is 2. Conversely, if β_2 is not significantly different from zero, we estimated the model again setting down the polynomial degree to 1. According to the significance of β_1 we concluded the degree of the polynomial to be either 1 or zero. In the latter case the expected yield corresponds to the mean of the series.

In this detrending exercise, we apply the MM estimator, which has been introduced by Yohai (1987) and combines the high efficiency of the M estimator (Huber, 1964) with the highest possible breakdown point (0.5) of the S estimator (Rousseeuw and Yohai, 1984). The idea of the MM estimator is to use a weight function to bound the influence of outlying observations. The MM estimator finds the vector of parameter estimates $\hat{\boldsymbol{\beta}}$ which minimises the function:

$$\min_{\hat{\boldsymbol{\beta}}} \sum_{t=1}^{T} \rho_1\left(\frac{e_{cit}(\hat{\boldsymbol{\beta}})}{\sigma}\right) \tag{1}$$

where ρ_1 is the loss function and σ is the robust residual scale parameter which measures the dispersion of the regression residuals.

[2] We have tried to set the maximum polynomial degree at a level larger than 2. However, several outlier observations at the end of the series benefitted from the tails of such polynomials. Indeed, even though the MM estimator is robust to outliers the tails of a polynomial degree larger than 2 mask the outliers at the beginning and at the end of the series such that they are no longer detected as outliers. To overcome this problem, we decided to allow the polynomial degree to be not larger than 2.

Differentiating equation 1 with respect to the vector of unknown parameters $\boldsymbol{\beta}$, we have:

$$\sum_{t=1}^{T} \psi\left(\frac{e_{cit}(\hat{\boldsymbol{\beta}})}{\sigma}\right)t = 0 \tag{2}$$

where, ψ is the first order derivative of the loss function ρ_1.

Equation (2) is solved by Iterative Weighted Least Squares (IRWLS) (see Chapter 4 of Maronna, Martin and Yohai, 2006, for a detailed explanation of IRWLS). The general idea of this procedure is that robust starting values for the regression coefficients ($\hat{\boldsymbol{\beta}}$) and for the scale (σ) are first employed, then the residuals $e_t(\hat{\boldsymbol{\beta}})$ and the associated weights are computed, and finally the model is re-estimated rescaling the residuals with the new weights. In each iteration, the residuals and the associated weights are updated. The larger a residual is, the lower its weight will be in the following run such that when the procedure stops the outlying observations have a very small or even zero weight. The procedure stops when the difference in the argument of equation (1) between two consecutive iterations is smaller than a predefined small number. The robust starting values for $\hat{\boldsymbol{\beta}}$ and σ which enter the IRWLS estimation are obtained by a S estimator, which is defined as:

$$\frac{1}{T}\sum_{t=1}^{T} \rho_0\left(\frac{e_t(\hat{\boldsymbol{\beta}})}{\sigma}\right) = \delta \tag{3}$$

and

$$\min_{\hat{\boldsymbol{\beta}}} \sigma(e(\boldsymbol{\beta})) \tag{4}$$

where, ρ_0 is the loss function of the S estimator and $\delta \in (0,1)$ is the tuning constant which determines the breakdown point of the scale estimator σ. Equation (3) results in the minimum value of σ for each given value of $\hat{\boldsymbol{\beta}}$, while equation (4) finds the vector $\hat{\boldsymbol{\beta}}$ that results in the lowest σ.

We employed a Tukey's bisquare loss function in the MM estimator which is defined as:

$$\rho(v) = \begin{cases} 1-(1-(v/k)^2)^3 & \text{if } |v| \le k \\ 1 & \text{if } |v| \ge k \end{cases} \tag{5}$$

where k is a tuning constant. The tuning constant for the loss function of the S estimator (ρ_0) is set to 1.548, such that the breakdown point of the estimator is 0.5. The tuning constant for the loss function of the M estimator (ρ_1) is set to 4.685, such that the regression estimator shows an asymptotic efficiency of 95% (Maronna, Martin and Yohai, 2006).

The estimation is run by benefitting of the *robustbase* package of the R software (Basic Robust Statistics, 2016).

We applied the MM estimator to each individual country-crop yield series, such that the regression parameter estimates are country-crop specific. As already stated in the Introduction, the use of an estimator that is robust to outliers is important to get an unbiased measure of the random component of yield in the following step.

It is noteworthy that while we want to prevent the trend estimates to be affected by outlying observations, the outliers have not to be dropped from the analysis, but rather they contribute to the random part of the yield. Indeed, while the trend can be interpreted as “the average tendency” (and thus its estimation requires an outlier free series), the yield variability must include all kind of variation, including the extreme variations represented by outliers. An MM estimator allows to have a yield trend that is not contaminated by outliers and let the outliers effect to be completely reflected in the random component of yield.

3.2 Crop yield variability

Once each country-crop yield series was estimated, we computed the crop yield variability at country-crop level ($yrisk_{cit}$) by:

$$yrisk_{ci} = \frac{\sum_{t=1}^{T} | y_{cit} - E(y_{cit}) |}{T * median_{ci}} \qquad (6)$$

where $E(y_{cit})$ and $median_{ci}$ are the expected value of the country-crop yield series from the MM regression and the median of the series respectively and T is the total number of observations for the series (the number of years when the crop yield is reported). When computing yield variability each observation is considered equally influential on the variability. Thus, an outlier observation that has a zero weight in the MM trend estimation enters equally to the other observations in the computation of the variability, such that its effect is completely reflected in the random part of yield. The normalisation by the median of the series allows to make this yield variability measure comparable across countries and across crops. Indeed, the measure is free from any unit of measurement. In addition, the advantage of normalising by the median compared to the mean lies on the fact that the median is an outlier-free measure and thus it reflects better the order of magnitude of the series and allow the outlying observations to be captured completely by the numerator of the formula.

As the next step was to compute the Analysis of Variance (ANOVA) also over time, for each country-crop series we computed the yield risk measure of equation (6) for two decades separately. Thus each series has two measures of yield variability, one for the decade 1992-2002 and one for the decade 2003-2013. Although for many series (78% of the total number of series considered in this study) data are available since 1961, a rather large percentage of series (11%) started to be reported since 1992. We, thus, preferred to restrict our ANOVA to the last two decades of the data.

3.3 ANOVA

As the total number of country-crop combinations we consider is 8,088, it was impossible to perform pairwise comparisons of the yield variability measure ($yrisk_{cit}$). In order to deal with such a large number of combinations, we performed an ANOVA, considering as "treatments" the country aggregates, the crop aggregates and the decades. The ANOVA allows to check the null hypothesis of no effect of a treatment on explaining the yield risk (measured by equation (6)) against the alternative of statistically significant differences due to the treatment. We adopted a geographical aggregation of countries following the macro-regions classification identified by the World Bank. In Tables A1 of the Appendix the list of countries in each macro-region is reported. Equally we grouped crops into crop aggregates which were used as another treatment in the ANOVA. For the list of crops belonging to each crop aggregate refer to Table A2 in the Appendix. The third treatment considered in the ANOVA has only two levels (1992-2002, 2003-2013) and is represented by the two last decades of the data.

According to the ANOVA, the variable $yrisk_{cid}$ can be decomposed into:

$$yrisk_{cid} = \mu + \alpha_{ca} + \eta_{ia} + \delta_{d} \tag{7}$$

Where, ca is the country aggregate of country c, ia is the crop aggregate of crop i, d indicates the decade, μ is the overall mean of $yrisk_{ci}$ across all the country-crop series, α_{ca} is yield risk explained by belonging to the country aggregate ca, η_{ia} is yield risk described by belonging to the crop aggregate ia and δ_{d} is yield risk explained by the decade for which $yrisk$ is computed.

The ANOVA test compares the variation of the yield risk measure across groups (where each group is identified by country aggregates, crop aggregates and decades) with the variation of the yield risk measure within each group. Specifically:

a) the overall group variation is computed as:

$$SS_{overall} = \sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{d=1}^{2}(yrisk_{cid} - \overline{yrisk})^2 \tag{8}$$

where $\overline{yrisk}$ is the overall mean of the yield risk measure across countries, crops and decades;

b) the between group variation for country aggregates is computed as:

$$SS_{country\_aggregate} = \sum_{ca=1}^{CA}\left[n_{ca}\sum_{i=1}^{I}\sum_{d=1}^{2}(\overline{yrisk}_{id}^{ca} - \overline{yrisk})^2 \right] \tag{9}$$

where, CA is the total number of country aggregates, n_{ca} is the number of country-crop series in the country aggregate ca, $\overline{yrisk}_{id}^{ca}$ is the average of the yield risk for crop i in decade d across all countries belonging to the country aggregate ca;

c) the between group variation for crop aggregates is computed as:

$$SS_{item\_aggregate} = \sum_{ia=1}^{IA}\left[n_{ia} \sum_{c=1}^{C}\sum_{d=1}^{2} (\overline{yrisk}_{cd}^{ia} - \overline{yrisk})^2 \right] \tag{10}$$

where, IA is the total number of crop aggregates, n_{ia} is the number of country-crop series in the crop aggregate ia and $\overline{yrisk}_{cd}^{ia}$ is the average of the yield risk for crop aggregate ia in decade d across all crops belonging to the crop aggregate ia;

d) the between group variation for the decades is computed as:

$$SS_{decade} = 2 \cdot \left[n_d \sum_{c=1}^{C}\sum_{i=1}^{I} (\overline{yrisk}_{ci}^{d} - \overline{yrisk})^2 \right] \tag{11}$$

where, n_d is the number of country-crop series in the decade d and $\overline{yrisk}_{ci}^{d}$ is the average of the yield risk for decade d across all country-crop series;

e) the within group variation is computed as:

$$SS_{within} = SS_{overall} - SS_{country\_aggregate} - SS_{crop\_aggregate} - SS_{decade} \tag{12}$$

The ANOVA compares the above measures. More specifically:

a) the country aggregate contributes significantly to explain crop yield variability if:

$$\frac{\dfrac{SS_{country\_aggregate}}{CA-1}}{\dfrac{SS_{within}}{C \cdot I \cdot 2 - CA + 1}} \geq F_{\alpha, CA-1, C \cdot I \cdot 2 - CA + 1} \tag{13}$$

b) the crop aggregate contributes significantly to explain yield variability if :

$$\frac{\dfrac{SS_{crop\_aggregate}}{IA-1}}{\dfrac{SS_{within}}{C \cdot I \cdot 2 - IA + 1}} \geq F_{\alpha, IA-1, C \cdot I \cdot 2 - IA + 1} \tag{14}$$

c) the decade contributes significantly to explain the yield variability if :

$$\frac{SS_{decade}}{\dfrac{SS_{within}}{C \cdot I \cdot 2 - 1}} \geq F_{\alpha, 1, C \cdot I \cdot 2 - 1} \tag{15}$$

For the first seven most worldwide grown crops in terms of acreages, namely wheat, rice, barley, corn, millet, sorghum and soybeans, we also performed the ANOVA on each crop. In this case, the ANOVA include only two treatments (country aggregate and decades) and analyses the influence of the country aggregate and of the decade on yield variability for each of the seven crops separately.

3.4 Tukey HSD test

If the results of the ANOVA indicate a statistically significant contribution of at least one of the treatment, it is interesting to perform pairwise comparisons to shed light on which pairs of treatment levels are responsible for the results of the ANOVA. As two of the treatments we considered (country aggregate and crop aggregate) have more than two levels the issue of multiple comparison arises. Indeed, running L independent tests at a α significance level, the probability of accepting the null hypothesis (assuming it is true) in all of the L comparisons is $(1-\alpha)^{L}$. Thus, some correction for this multiplicity effect must be adopted. One test which accounts and correct for the multiplicity effect is the Honestly Significant Difference (HSD) Tukey test. The Tukey test compares the difference between the means of group 1 and group 2 ($\left|\overline{yrisk}_1 - \overline{yrisk}_2\right|$) with the following measure:

$$T = q_{\alpha,L,n_T-L}\sqrt{s^2(\frac{n_1+n_2}{2n_1n_2})}$$

where, α is the significance level, n_T is the sum of the observations in the two groups (n_1+n_2), q is the studentized range distribution and s^2 is the sample variance. If $\left|\overline{yrisk}_1 - \overline{yrisk}_2\right| > T$ then the two group means are statistically different.

We adopted the HSD Tukey test to perform pairwise comparisons between pairs of country aggregates and pairs of crop aggregates. The comparison between the two decades did not require any additional test, as in the case of two-level treatment the results of the ANOVA directly indicate the statistical significance of the difference between the two levels.

4. DATA

Crop yield data series come from the FAO database, a large worldwide database which collects annually national data on agricultural production and food consumption as well as on agricultural trade and prices, on inputs use in the agricultural sector and on some environmental variables. The Production section of the database contains data on production and acreages for 168 crops over 224 countries and it is the most comprehensively world database for agricultural production data. For 78% of the 10,532 country-crop combinations, production data are available since 1961, while for the remaining combinations data collection starts later according to the series (50% of the remaining series starts to be recorded in 1992). 2013 is the last year we considered in our analysis as data for 2014 were available only for a handful of country-crop combinations at the time the study was implemented.

In our study we considered the 141 crops belonging to the crop aggregates: cereals, citrus fruit, fruit, nuts, oilcrops, pulses, roots and tubers, spices, sugar and vegetables. We did not consider the 27 crops from the fibre crops, oils, seeds and other aggregates. Following the World Bank classifications, the geographical aggregation identified 7 groups (East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, Sub-Saharan Africa).

We dropped from this study the 818 (8.8%) country-crop yield series where data are reported for less than 11 years. Indeed, short time series are likely to result in unreliable trends and measures of yield variability.

Before estimating the deterministic trend individually for each country-crop yield series, we detected the presence of typing errors in the series. The observations that showed a typing error were dropped from the study. The typing errors were detected by comparing each yield value with its neighborhood values in that country-crop series. If a yield value is ‘too far away’ from its neighbors such that it likely belongs to a mechanism (typing errors) different from the one defining its neighbors, then we classified that observation as a typing error. The threshold was set equal to 6 times and 1/6 times of its neighbors. Out of 394,596 observations where yield data are available, we found only 9 observations where yield can be classified as typos leading to too large values according to our criteria and 41 observations where yield can be classified as typos leading to too small values. One may argue that while a yield larger than 6 times its neighbors is not realistic and is certainly a typing error, weather events may lead to a sharp drop in production such that a yield lower than 1/6 of its last and next year yield may actually happen. In order to prevent this, we checked manually all the 41 observations and, where it was clear that the yield values contained a typing error, we dropped that observation.

During the estimation process 140 country-crop series (1.65%) did not reach convergence either in the S estimator step or in the M estimator step. This series were dropped from the analysis. We also dropped from the analysis the 231 series (2.73%) which reported exactly the same yield values for more than 50% of the observations. Indeed, it is likely that in this case the reported yields are not the actual ones but are imputed. The final number of series considered in our analysis is 8,088.

Looking at the share of each crop aggregate across country aggregates, the East Asia and Pacific group displays the highest share for most of the crop aggregates considered (Table 1). The three exceptions are represented by pulses and by spices, whose highest share is covered by South Asia, and by sugar, where Europe and Central Asia ranks the top. The lowest share for the crop aggregates are displayed either by the Middle East and North Africa group or by the North America group.

If we consider the number of individual country-crop combinations in each aggregate, the Europe and Central Asia group shows the highest number of series for most of the crop aggregates, the Sub-Saharan Africa ranks the top in terms of the number of series for spices and roots and tubers group and the Latin American and Caribbean group for citrus fruit. North America is the group which has the lowest number of series for all crop aggregates among the country groups. Vegetables have the largest number of country-crop series (around 25% of the total series) followed by fruit (24%) and cereals (12.5%).

Table 2 presents the acreage share at the disaggregated level of single crop for the seven mostly grown crops in the world. While barley and wheat are largely grown in Europe and Central Asia, the East Asia and Pacific group represents the largest share among the geographical aggregates for corn (24.5%) and rice (50.9%). North America ranks the top for the acreages allocated to soybeans (41.4%). 80% of the millet area is grown in South Asia and Sub-Saharan Africa, which is also the first country aggregate for the area allocated to sorghum. For three of the seven crops the Middle East and North Africa group has a share lower than 1%.

Table 1. Acreage share of the crop aggregates in each country aggregate and number of individual crop-country series in each crop aggregate-country aggregate combination (geographical country aggregation).

	East Asia and Pacific		Europe and Central Asia		Latin American and Caribbean		Middle East and North Africa		North America		South Asia		Sub-Saharan Africa	
	share*	n^	share	n	share	n	share	n	share	n	share	n	share	n
cereals	25.8	120	29.4	377	6.0	133	3.3	93	10.1	18	15.9	38	9.3	233
citrus fruit	22.0	59	9.9	53	27.8	120	9.1	68	6.9	5	9.3	21	15.1	83
fruit	24.3	272	34.2	613	10.2	374	6.4	272	2.4	40	8.8	73	13.8	278
nuts	19.4	37	22.1	108	11.8	28	9.1	33	4.6	5	13.0	19	20.0	41
oilcrops	24.3	121	15.5	235	14.1	136	2.0	68	18.7	16	15.0	42	10.5	192
pulses	14.8	56	14.7	218	10.6	97	2.5	89	2.5	10	34.3	31	20.6	130
roots and tubers	30.0	112	27.9	58	7.6	159	0.8	31	1.3	6	3.5	20	29.0	170
spices	19.4	54	2.9	39	3.2	48	3.5	19	0.3	2	49.5	28	21.2	86
sugar	16.3	21	30.2	43	28.2	39	1.6	16	3.2	3	16.8	10	3.6	35
vegetables	40.6	274	19.7	675	5.2	376	5.0	319	3.8	41	15.0	64	10.7	285

* the share measures the number of acreages of the crop aggregate in the country aggregate over the total acreages grown in the world for that crop aggregate

^ n indicates the number of individual country-crop series in each crop aggregate-country aggregate combination

Table 2. Acreage share of each crop and number of countries where the crop is grown in each country aggregate (geographical country aggregation).

	East Asia and Pacific		Europe and Central Asia		Latin American and Caribbean		Middle East and North Africa		North America		South Asia		Sub-Saharan Africa	
	share*	n^	share	n	share	n	share	n	share	n	share	n	share	n
Wheat	22.9	12	42.8	48	3.4	13	5.5	19	12.3	2	11.8	6	1.3	26
Rice	50.9	22	0.8	19	4.5	27	0.7	6	0.8	1	38.3	6	3.9	40
Barley	17.0	10	60.9	48	1.3	10	8.6	17	7.7	2	2.2	5	2.3	12
Corn	24.5	24	12.8	39	18.9	35	1.0	14	20.5	2	5.9	7	16.4	46
Millet	11.0	9	8.4	25	0.2	2	0.4	8	0.3	1	40.2	8	39.5	36
Sorghum	7.9	13	0.6	20	7.8	19	2.2	12	9.2	1	29.8	4	42.5	39
Soybeans	18.3	15	3.0	26	30.2	17	0.1	3	41.4	2	5.8	5	1.2	21

* the share measures the number of acreages of the crop in the country aggregate over the total acreages of that crop grown in the world

^n indicates the number of individual country-crop series in each crop aggregate-country aggregate combination

5. RESULTS

5.1 Order of the polynomial yield trend

As we allowed for a flexible polynomial yield trend where the degree was selected during the estimation process, each individual country-crop series may display a different polynomial order. Out of 8,088 single country-crop combinations, 53.8% identified a polynomial trend of order two, 32.7% of order one and the remaining 13.5% have no trend (Table 3). The second order trend polynomial is also the most frequently recorded in each crop aggregate. Among the country-crop series exhibiting a linear trend, the increasing trend is largely more observed than the decreasing trend (from 60% to 88% of all the series in each crop aggregate). Among the series displaying a second order polynomial trend, the ratio between the ones with a U-shape and the ones with an inverse U-shape is around 1.3 in all the aggregates, except for the spices aggregate where this ratio is 1.8. The heterogeneity in the yield trend in the series underlines the need to carefully check the shape and the sign of the yield trend when the trend is included in larger models such as partial equilibrium or general equilibrium models. Additionally, it also drives the attention on potential mistakes in estimating the yield trend on crop aggregates, which are likely to mix crops with heterogenous trends.

If we analyse the yield trend estimates considering simultaneously the geographical country aggregates and the crop aggregates, we notice that the second order polynomial trend is the most frequently estimated trend in most country aggregate-crop aggregate combinations (Table 4). The exceptions are represented by North America, where most of the series belonging to nuts, oilcrops, pulses and roots and tubers display a linear trend, and by Europe and Central Asia, where the linear trend is most frequently estimated for oilcrops and pulses. The linear trend is.

Table 3. Number of country-crop series in the crop aggregates for each order and sign of the polynomial yield trend

Order of the trend polynomial	0		1						2					
			total		B_1 positive		B_1 negative		total		B_2 positive		B_2 negative	
	n.	%	n.	% ^	n.	% °	n.	% °	n.	%^	n.	% °	n.	%°
cereals	137	13.5	362	35.8	317	87.6	45	12.4	513	50.7	288	56.1	225	43.9
citrus fruit	51	12.5	123	30.1	76	61.8	47	38.2	235	57.5	130	55.3	105	44.7
fruit	255	13.3	623	32.4	423	67.9	200	32.1	1044	54.3	585	56.0	459	44.0
nuts	36	13.3	105	38.7	72	68.6	33	31.4	130	48.0	76	58.5	54	41.5
oilcrops	126	15.6	281	34.7	204	72.6	77	27.4	403	49.8	230	57.1	173	42.9
pulses	117	18.5	211	33.4	182	86.3	29	13.7	303	48.0	179	59.1	124	40.9
roots and tubers	61	11.0	170	30.6	125	73.5	45	26.5	325	58.5	180	55.4	145	44.6
spices	33	12.0	76	27.5	62	81.6	14	18.4	167	60.5	107	64.1	60	35.9
sugar	16	9.6	60	35.9	43	71.7	17	28.3	91	54.5	51	56.0	40	44.0
vegetables	258	12.7	637	31.3	486	76.3	151	23.7	1139	56.0	635	55.8	504	44.2

^ this percentage is the ratio between the number of series of that order of polynomial in the crop aggregate over the total number of series in the same crop aggregate

° this percentage is the ratio between the number of series of that order and sign of the polynomial in the crop aggregate over the total number of series of that order of polynomial in the same crop aggregate

Table 4. Number of country-crop series in each crop aggregate-country aggregate for each order of the polynomial trend

	East Asia and Pacific			Europe and Central Asia			Latin American and Caribbean			Middle East and North Africa			North America			South Asia			Sub-Saharan Africa		
Order of the polynomial trend	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2
cereals	14	32	74	73	154	150	6	41	86	17	27	49	1	10	7	3	10	25	23	88	122
citrus fruit	2	9	48	9	18	26	17	38	65	9	26	33	1	1	3	2	7	12	11	24	48
fruit	21	80	171	103	242	268	44	104	226	33	85	154	3	17	20	11	19	43	40	76	162
nuts	2	15	20	15	37	56	5	13	10	3	17	13	0	3	2	3	8	8	8	12	21
oilcrops	11	38	72	54	97	84	20	43	73	8	23	37	3	10	3	3	15	24	27	55	110
pulses	8	17	31	55	83	80	10	31	56	20	33	36	1	6	3	3	9	19	20	32	78
roots and tubers	13	33	66	6	21	31	17	44	98	3	12	16	0	5	1	3	7	10	19	48	103
spices	6	11	37	3	18	18	5	18	25	2	6	11	1	0	1	1	7	20	15	16	55
sugar	1	6	14	5	23	15	7	9	23	1	7	8	0	0	3	0	5	5	2	10	23
vegetables	28	87	159	93	214	368	48	107	221	31	109	179	1	18	22	5	16	43	52	86	147

also the most frequently estimated trend for nuts in Latin America and Caribbean and in the Middle East and North Africa

5.2 Three-way ANOVA

The results of the ANOVA (Table 5) indicates that all the three treatments considered in the analysis, namely the geographical country aggregate, the crop aggregate and the decade, contribute to explain the yield risk measure. In order to gain knowledge on which pairs of country aggregates and on which pairs of crop aggregates are statistically different in terms of yield risk we performed a HSD Tukey pairwise comparison. The comparison (Table 6) indicates that the yield risk in the Middle East and North Africa aggregates is statistically different from the yield risk estimated in each of the other country aggregates. As the mean of the yield risk in this geographical area is the highest among the country aggregates (Table 8) we can conclude that Middle East and North Africa is the most agricultural risky area. Our measure for yield variability in this area is 73% higher than the value estimated in North America, which appears to be the lowest risky area, and 24% higher than Europe and Central Asia and Latin American and Caribbean, which are the second most risky country aggregates. None of the other pairwise comparisons result in statistically significant differences, indicating that the yield risk in the other geographical areas is not statistically different. This result confirms the high sensitivity of crop yields to the weather and to other natural events in the Middle East and North Africa region and it claims the urgency for the international community and for local governments to take actions in this area to face this high yield uncertainty.

The results of the pairwise comparisons between crop aggregates indicates that crop aggregates is less responsible in explaining yield variability compared than country aggregate (Table 7). Indeed, the only two statistically significant differences concern sugar (the less risky

Table 5. Results of the three-way ANOVA (geographical country aggregation)

	Sum of squares	Degrees of freedom	F test	p-value
$SS_{country\_aggregate}$	7.4	6	3.9	0.001***
$SS_{crop\_aggregate}$	6.5	9	2.3	0.015**
SS_{decade}	6.7	1	21.2	0.000***
SS_{within}	4,946.5	15,583		

Table 6. Differences in the means of the yield variability measure between each pair of country aggregates and significance level of this difference according to the HSD Tukey test

	East Asia and Pacific	Europe and Central Asia	Latin American and Caribbean	Middle East and North Africa	North America	South Asia
Europe and Central Asia	0.005^					
Latin American and Caribbean	0.005	0.000				
Middle East and North Africa	0.051*	0.046**	0.0463*			
North America	-0.052	-0.057	-0.057	-0.1035*		
South Asia	-0.035	-0.039	-0.039	-0.086***	0.018	
Sub-Saharan Africa	-0.013	-0.018	-0.018	-0.065***	0.039	0.021

^ This value is computed as the difference of the means of the yield variability measure between the country aggregate on the row and the country aggregate on the column

Table 7. Differences in the means of the yield variability measure between each pair of crop aggregates and significance level of this difference according to the HSD Tukey test

	cereals	citrus fruit	fruit	nuts	oilcrops	pulses	roots and tubers	spices	sugar
citrus fruit	0.009^								
fruit	0.018	0.008							
nuts	0.045	0.036	0.028						
oilcrops	0.043	0.034	0.025	-0.002					
pulses	0.015	0.006	-0.002	-0.030	-0.028				
roots and tubers	-0.001	-0.010	-0.019	-0.046	-0.044	-0.016			
spices	0.005	-0.004	-0.012	-0.040	-0.038	-0.010	0.006		
sugar	-0.078	-0.087	-0.095	-0.123*	-0.121**	-0.093	-0.077	-0.083	
vegetables	-0.008	-0.017	-0.026	-0.053	-0.051	-0.023	-0.007	-0.013	0.070

^ This value is computed as the difference of the means of the yield variability measure between the crop aggregate on the row and the crop aggregate on the column

Table 8. Mean and standard deviation of the yield variability measure and number of country-crop series in each aggregate

Country Aggregation	mean	st. dev.	n	Crop Aggregation	mean	st. dev.	n	Decades	mean	st. dev.	n
East Asia and Pacific	0.192	0.438	2,205	cereals	0.186	0.239	1,924	1992-2002	0.175	0.235	7,866
Europe and Central Asia	0.197	0.449	4,480	citrus fruit	0.199	0.383	811	2003-2013	0.217	0.763	7,790
Latin American and Caribbean	0.197	0.410	2,996	fruit	0.207	0.920	3,760				
Middle East and North Africa	0.244	1.199	1,978	nuts	0.233	0.397	535				
North America	0.140	0.160	288	oilcrops	0.227	0.748	1,531				
South Asia	0.158	0.290	685	pulses	0.204	0.310	1,192				
Sub-Saharan Africa	0.179	0.283	3,024	roots and tubers	0.182	0.342	1,093				
				spices	0.186	0.306	539				
				sugar	0.107	0.090	316				
				vegetables	0.183	0.293	3,955				

crop aggregate) with nuts and with oilcrops (the two crop aggregates with the highest yield variability). Finally, as only two decades are included (1992-2002 and 2003-2013), the results of the ANOVA already indicate a significant difference in the yield variability between the two decades. In particular, the decades with the highest variability is the 2003-2013 showing an increase in the yield risk over time.

5.3 Two-way ANOVA on the most grown crops

The ANOVA on each of the seven worldwide most grown crops shows heterogenous results. The geographical country aggregate affects the measure of yield risk in all the crops but soybeans while the decade has an effect on corn and on sorghum yield risk only (Table 9).

For each of the seven crops we compared the yield risk between pairs of country aggregates by the HSD Tukey test (Table 10), although results should be taken with some cation. North America exhibits the lowest yield risk for all the crops grown in the area (wheat, barley, corn, soybeans). However, for none of the crops the yield risk measure in North America is statistically different from the values estimated in the other country aggregates. This surprising result lies on the very small number of observations for each crop in North America, which is composed by only three countries, namely Canada, US and Mexico. The smaller sample size (Table 11) compared to the other country aggregates leads to a large sample variance for the yield risk measure in North America which in turns determines the absence of statistical significance in the pairwise comparisons. The increase in the sample variance due to the small sample size is also recorded for South Asia, where the number of observations ranges between 4 and 8 according to the crop. As a result, although for rice and sorghum the South Asia country aggregate shows the lowest yield uncertainty, it does not

Table 9. Results of the two-way ANOVA on each of the seven most grown crops at world level (geographical country aggregation)

		Sum of squares	Degrees of freedom	F test	p-value
wheat	$SS_{country\_aggregate}$	0.5	6	4.9	0.000***
	SS_{decade}	0.0	1	0.0	0.937
	SS_{within}	4.4	237		
rice	$SS_{country\_aggregate}$	0.5	5	3.8	0.003***
	SS_{decade}	0.0	1	0.5	0.493
	SS_{within}	5.5	221		
barley	$SS_{country\_aggregate}$	0.4	6	3.4	0.003***
	SS_{decade}	0.0	1	0.0	0.879
	SS_{within}	3.8	193		
corn	$SS_{country\_aggregate}$	3.2	6	3.2	0.005***
	SS_{decade}	0.7	1	4.4	0.037**
	SS_{within}	52.8	313		
millet	$SS_{country\_aggregate}$	0.4	5	3.3	0.008***
	SS_{decade}	0.0	1	0.3	0.597
	SS_{within}	3.8	158		
sorghum	$SS_{country\_aggregate}$	1.7	5	4.1	0.001***
	SS_{decade}	0.2	1	3.0	0.086*
	SS_{within}	16.4	200		
soybeans	$SS_{country\_aggregate}$	0.8	6	1.4	0.210
	SS_{decade}	0.2	1	2.3	0.128
	SS_{within}	14.7	161		

display a statistical difference in the measure of yield variability from the other country aggregates.

Middle East and North Africa and Sub-Saharan Africa are the two country aggregates with the highest yield variability for wheat and barley (Table 11) and their variability is statistically different from the ones in Europe and Central Asia which is the second-last country aggregate in terms of variability for these two crops. The yield variability in Middle East and North Africa is 96% and 84% higher than the variability in Europe and Central Asia for wheat and barley respectively, while the variability in Sub-Saharan Africa is 84% and 68% higher respectively.

Sub-Saharan Africa is also the most risky area for rice yield and its measure is statistically different from East Asia and Pacific (104% higher) and from Europe and Central Asia (74% higher), respectively the second last and the third last group in terms of yield risk for rice. Middle East and North Africa group shows the highest yield uncertainty for sorghum, which is statistically different from all the other country aggregates, but South Asia (due again to the small number of observations).

South Asia is the most risky country aggregate for corn and its measure of yield uncertainty significantly differ from all the other countries but Middle East and North Africa (which is the second most risky country aggregate for corn) and North America (for the large sample variance due to the small number of observations).

The highest yield uncertainty for millet is estimated in Europe and Central Asia, where the value is more than double of the one recorded in East Asia and Pacific and 64% higher than the one of Sub-Saharan Africa. No statistical significant differences are registered for the other country aggregates.

The pairwise comparison for soybeans confirms the absence of an effect of the country aggregate on explaining the yield variability as none of the pairs shows statistical significant differences.

The ANOVA indicates an effect of the decade on the yield risk for corn and sorghum only. Looking at the mean value of the yield variability measure for these two crops in each decade, we can conclude that yield variability increased from 1992-2002 to 2003-2013 by 50% for corn and by 36% for sorghum (Table 12).

6. CONCLUSIONS

Food security is one of the 17 SDGs set in 2015 by the international community and it is the basis to reach many of the other SDGs. One of the threat to food security is the variability of crop yield due to weather and other natural events, which make farmer income highly unstable and local population highly vulnerable. By assessing the yield variability and comparing it across geographical regions and across crops, agricultural economists provide the international community with analytical insights on where the most urgent efforts should be addressed.

We performed this comparison by conducting an analysis on national yield data for 141 crops and 224 countries recorded in the FAO database. Many yield series are available since 1961, while other series started to be reported later. The first step of our analysis consisted in the estimation of the yield trend for each single country-crop series by means of a robust estimator, the MM estimator. Robust estimator prevents the yield trend to be biased by the potential presence of outliers, which should be completely captured by the yield variability measure. Then, a yield variability measure was computed for each country-crop series and the contribution of country aggregates, crop aggregates and time on explain the yield variability was analysed by a

Table 10. Differences in the means of the yield variability measure between each pair of country aggregate and significance level of this difference according to the HSD Tukey test

	East Asia and Pacific	Europe and Central Asia	Latin American and Caribbean	Middle East and North Africa	North America	South Asia	East Asia and Pacific	Europe and Central Asia	Latin American and Caribbean	Middle East and North Africa	North America	South Asia
wheat							**rice**					
Europe and Central Asia	-0.037^						0.018					
Latin American and Caribbean	0.020	0.057					0.033	0.015				
Middle East and North Africa	0.075	0.11***	0.055				0.077	0.059	0.044			
North America	-0.076	-0.039	-0.096	-0.151			n.a.	n.a.	n.a.	n.a.		
South Asia	-0.029	0.009	-0.049	-0.103	0.047		-0.019	-0.037	-0.052	-0.096	n.a.	
Sub-Saharan Africa	0.061	0.10***	0.041	-0.013	0.137	0.090	0.106***	0.088*	0.073	0.028	n.a.	0.124
corn							**millet**					
Europe and Central Asia	-0.081						0.138**					
Latin American and Caribbean	0.025	0.106					0.007	-0.131				
Middle East and North Africa	0.088	0.169	0.063				0.104	-0.034	0.097			
North America	-0.160	-0.079	-0.185	-0.248			n.a.	n.a.	n.a.	n.a.		
South Asia	0.42**	0.50***	0.394**	0.331	0.579		0.061	-0.077	0.054	-0.043	n.a.	
Sub-Saharan Africa	-0.006	0.076	-0.031	-0.094	0.154	-0.4***	0.036	-0.102**	0.029	-0.068	n.a.	-0.025

Continued…

Table 10. Differences in the means of the yield variability measure between each pair of country aggregate and significance level of this difference according to the HSD Tukey test (…continued)

	East Asia and Pacific	Europe and Central Asia	Latin American and Caribbean	Middle East and North Africa	North America	South Asia	East Asia and Pacific	Europe and Central Asia	Latin American and Caribbean	Middle East and North Africa	North America	South Asia
barley							**soybeans**					
Europe and Central Asia	-0.047						0.103					
Latin American and Caribbean	-0.040	0.007					-0.017	-0.119				
Middle East and North Africa	0.056	0.10***	0.096				0.028	-0.075	0.045			
North America	-0.110	-0.063	-0.070	-0.166			-0.068	-0.171	-0.052	-0.096		
South Asia	-0.025	0.022	0.015	-0.081	0.085		0.241	0.138	0.258	0.213	0.310	
Sub-Saharan Africa	0.045	0.092*	0.085	-0.011	0.155	0.070	0.041	-0.061	0.058	0.013	0.110	-0.200
sorghum												
Europe and Central Asia	0.063											
Latin American and Caribbean	-0.006	-0.069										
Middle East and North Africa	0.3***	0.215*	0.283***									
North America	n.a.	n.a.	n.a.	n.a.								
South Asia	-0.073	-0.136	-0.067	-0.351	n.a.							
Sub-Saharan Africa	0.005	-0.058	0.011	-0.273***	n.a.	0.078						

Table 11. Mean and standard deviation of the yield variability measure and number of country-crop series in each aggregate

	Mean (standard deviation in parenthesis)							Number of series						
	wheat	rice	barley	corn	millet	sorghum	soybeans	wheat	rice	barley	corn	millet	sorghum	soybeans
East Asia and Pacific	0.15 (0.09)	0.10 (0.09)	0.18 (0.13)	0.23 (0.38)	0.12 (0.07)	0.18 (0.15)	0.14 (0.15)	12	21	10	23	9	13	13
Europe and Central Asia	0.12 (0.08)	0.12 (0.09)	0.13 (0.12)	0.15 (0.14)	0.26 (0.17)	0.25 (0.21)	0.25 (0.51)	45	17	45	35	20	17	24
Latin American and Caribbean	0.17 (0.26)	0.13 (0.10)	0.14 (0.07)	0.26 (0.55)	0.13 (0.05)	0.18 (0.24)	0.13 (0.06)	13	26	10	34	2	19	17
Middle East and North Africa	0.23 (0.16)	0.18 (0.11)	0.24 (0.16)	0.32 (0.22)	0.23 (0.13)	0.46 (0.66)	0.17 (0.09)	19	4.5	17	14	8	12	3
North America	0.08 (0.03)	n.a.	0.07 (0.02)	0.07 (0.03)	n.a.	n.a.	0.07 (0.02)	2	n.a.	2	2	n.a.	n.a.	2
South Asia	0.13 (0.10)	0.08 (0.07)	0.16 (0.12)	0.65 (1.29)	0.18 (0.30)	0.11 (0.07)	0.38 (0.35)	6	6	5	7	8	4	5
Sub-Saharan Africa	0.22 (0.14)	0.21 (0.23)	0.23 (0.23)	0.22 (0.17)	0.16 (0.12)	0.19 (0.17)	0.18 (0.13)	25	26	27	28	29	30	31

Table 12. Mean and standard deviation of the yield variability measure of country-crop series in each decade

	Mean							Standard deviation						
	wheat	rice	barley	corn	millet	sorghum	soybeans	wheat	rice	barley	corn	millet	sorghum	soybeans
2002-2012	0.16	0.14	0.17	0.19	0.18	0.19	0.16	0.13	0.12	0.13	0.19	0.13	0.20	0.14
2003-2013	0.17	0.16	0.17	0.29	0.19	0.26	0.23	0.15	0.20	0.16	0.57	0.19	0.37	0.41

three-way ANOVA. Pairwise comparison between country aggregates and between crop aggregates was conducted through the HSD Tukey test, which allows to correct for the multiplicity effect. Finally, the seven most grown crops (wheat, rice, barley, corn, millet, sorghum and soybeans), were analyzed individually by a two-way ANOVA and by pairwise comparisons between country aggregates.

Results indicate the influence of country aggregation on explaining crop yield variability. In particular, Middle East and North Africa region displays the highest variability and their yield risk is statistically higher than all the other regions. The yield risk in this area is estimated to be 73% higher than the yield risk in North America, the lowest risky area, and 24% higher than the second most risky country aggregates. The yield risk measure in the other country aggregates did not result to be statistically different from each other. In addition, the ANOVA indicates that, from 1992-2002 to 2003-2013, , yield variability increased by 20% at the world level .

Looking at the single crop series, for the seven most grown crops, yield risk of all crops but soybeans is affected by the geographical area. Middle East and North Africa and Sub-Saharan Africa are the two country aggregates with the highest yield variability for most crops and their variability measure is around 80-90% larger than the least risky aggregates. The only exceptions are represented by corn, where South Asia is the most risky country, and millet, where Europe and Central Asia ranks first. Soybeans did not show any difference in yield risky across country aggregates.

Although the use of national yield data to estimate yield variability may be questionable, due to the potential underestimation of variability, for the majority of countries they are the only available data. In addition, we argue that the potential underestimation does not affect the relative magnitude of the yield variability measure in one country compared to the others.

Based on our results, we can conclude that the collective actions of the international community, producers and civil society ought to urgently address the issue of yield variability mainly in Middle-East and North Africa and for many of the most grown crops also in Sub-Saharan Africa. High production uncertainty in these regions leads to unstable farmer income and food shortage which result, as a side effect, in poverty, health diseases, fight. The increase in yield variability over the years supports the need to take actions to avoid further increases in future decades and to move towards the realization of the SDGs.

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APPENDIX

Table A.1 List of countries and corresponding geographical country aggregate

East Asia and Pacific	*Europe and Central Asia*	*Latin America and Carabbean*	*Middle East and North Africa*	*North America*	*South Asia*	*Sub-Saharan Africa*
American Samoa	Albania	Antigua and Barbuda	Algeria	Bermuda	Afghanistan	Angola
Australia	Armenia	Argentina	Bahrain	Canada	Bangladesh	Benin
Brunei Darussalam	Austria	Bahamas	Djibouti	United States of America	Bhutan	Botswana
Cambodia	Azerbaijan	Barbados	Egypt		India	Burkina Faso
China	Belarus	Belize	Iran (Islamic Republic of)		Maldives	Burundi
Cook Islands	Belgium	Bolivia (Plurinational State of)	Iraq		Nepal	Cabo Verde
Democratic People's Republic of Korea	Belgium-Luxembourg	Brazil	Israel		Pakistan	Cameroon
Fiji	Bosnia and Herzegovina	British Virgin Islands	Jordan		Sri Lanka	Central African Republic
French Polynesia	Bulgaria	Cayman Islands	Kuwait			Chad
Guam	Croatia	Chile	Lebanon			Comoros
Indonesia	Cyprus	Colombia	Libya			Congo
Japan	Czech Republic	Costa Rica	Malta			Côte d'Ivoire
Kiribati	Czechoslovakia	Cuba	Morocco			Democratic Republic of the Congo
Lao People's Democratic Republic	Denmark	Dominica	Occupied Palestinian Territory			Equatorial Guinea
Malaysia	Estonia	Dominican Republic	Oman			Eritrea

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Marshall Islands	Faroe Islands	Ecuador	Qatar	Ethiopia
Micronesia (Federated States of)	Finland	El Salvador	Saudi Arabia	Ethiopia PDR
Mongolia	France	French Guiana	Syrian Arab Republic	Gabon
Myanmar	Georgia	Grenada	Tunisia	Gambia
Nauru	Germany	Guadeloupe	United Arab Emirates	Ghana
New Caledonia	Greece	Guatemala	Yemen	Guinea
New Zealand	Hungary	Guyana		Guinea-Bissau
Niue	Iceland	Haiti		Kenya
Pacific Islands Trust Territory	Ireland	Honduras		Lesotho
Papua New Guinea	Italy	Jamaica		Liberia
Philippines	Kazakhstan	Martinique		Madagascar
Republic of Korea	Kyrgyzstan	Mexico		Malawi
Romania	Latvia	Montserrat		Mali
Russian Federation	Liechtenstein	Nicaragua		Mauritania
Samoa	Lithuania	Panama		Mauritius
Singapore	Luxembourg	Paraguay		Mozambique
Solomon Islands	Montenegro	Peru		Namibia
Thailand	Netherlands	Puerto Rico		Niger
Timor-Leste	Norway	Saint Helena, Ascension and Tristan da Cunha		Nigeria
Tokelau	Poland	Saint Kitts and Nevis		Réunion
Tonga	Portugal	Saint Lucia		Rwanda
Tuvalu	Republic of Moldova	Saint Pierre and Miquelon		Sao Tome and Principe
Vanuatu	Serbia	Saint Vincent and the Grenadines		Senegal
Viet Nam	Serbia and Montenegro	Suriname		Seychelles

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Wallis and Futuna Islands	Slovakia	Trinidad and Tobago	Sierra Leone
	Slovenia	United States Virgin Islands	Somalia
	Spain	Uruguay	South Africa
	Sweden	Venezuela (Bolivarian Republic of)	South Sudan
	Switzerland		Sudan
	Tajikistan		Sudan (former)
	The former Yugoslav Republic of Macedonia		Swaziland
	Turkey		Togo
	Turkmenistan		Uganda
	Ukraine		United Republic of Tanzania
	United Kingdom		Western Sahara
	USSR		Zambia
	Uzbekistan		Zimbabwe
	Yugoslav SFR		

Table A.2 List of crops and corresponding crop aggregates

Cereals	*Citrus fruit*	*Fruit*	*Oilcrops*	*Nuts*	*Pulses*	*Roots and Tubers*	*Veetables*	*Sugar*	*Spices*
Barley	Grapefruit	Apples	Castor oil seed	Tung nuts	Bambara beans	Cassava	Artichokes	sugar cane	Pepper
Buckwheat	Lemons and limes	Apricots	Coconuts	Almonds, with shell	Beans, dry	Potatoes	Asparagus	sugar beet	Chillies and peppers, dry
Canary seed	Oranges	Avocados	Groundnuts, with shell	Brazil nuts, with shell	Broad beans, horse beans, dry	Roots and tubers, nes	Beans, green	Other sugar crops	Vanilla
Fonio	mandarins, clementines	Bananas	Hempseed	Cashew nuts, with shell	Chick peas	Sweet potatoes	Cabbages and other brassicas		Cinnamon
Maize	Others	Blueberries	Jojoba seed	Chestnut	Cow peas, dry	Taro (cocoyam)	Carrots and turnips		cloves
Millet		Carobs	Karite nuts (sheanuts)	Hazelnuts, with shell	Lentils	Yams	Cassava leaves		Nutmeg, mace and cardamoms
Oats		Cashewapple	Linseed	Pistachios	Lupins	Yautia (cocoyam)	Cauliflowers and broccoli		Anise, fennel, coriander
Other grains		Cherries	Melonseed	Walnuts, with shell	Peas, dry	Cassava	Chicory roots		Ginger
Quinoa		Cherries, sour	Mustard seed	Kola nuts	Pigeon peas	Potatoes	Chillies and peppers, green		Peppermint
Rice		Cranberries	Oil, palm fruit	Areca nuts	Pulses, nes	Roots and tubers, nes	Cucumbers and gherkins		Pyrethrum, dried
Rye		Currants	Olives	Others	Vetches	Sweet potatoes	Eggplants (aubergines)		Other spices
Sorghum		Dates	Poppy seed	Tung nuts		Taro (cocoyam)	Garlic		
Triticale		Figs	Rapeseed			Yams	Leeks, other alliaceous vegetables		
Wheat		Gooseberries	Safflower seed				Lettuce and chicory		

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Others	Grapes	Sesame seed		Maize, green
	Kiwi fruit	Soybeans		Mushrooms and truffles
	Mangoes, mangosteens, guavas	Sunflower seed		Okra
	Melons	Tallowtree seed		Onions, dry
		Others		Onions, shallots, green
	Papayas			
	Peaches and nectarines			Peas, green
	Pears			Pumpkins, squash and gourds
	Persimmons			Spinach
	Pineapples			String beans
	Plantains			Tomatoes
	Plums and sloes			Other Fresh Vegetables
	Quinces			Other Leguminous Vegetables
	Raspberries			
	Strawberries			
	Watermelons			
	Other fresh fruit			
	Other pome fruit			
	Other tropical fruit			

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