Has Agricultural Yield Growth Decelerated?

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By most accounts, yield growth of food commodities has decelerated during the past few decades (Grassini et al., 2013). Indeed, global grain yields, which grew by 3.3 percent annually during 1962-71, only grew by 2.3 percent during the past ten years. Such slowdown in yield performance has been cited as one of the key causes of the commodity price spikes of 2008 and 2011 (Piesse and Thirtle, 2009). Given that three-quarters of global food production growth during the past 55 years is a result of yield advancements, the deceleration has led to concerns regarding food availability, especially towards the middle of the current century when world's population is expected to reach 9.8 billion from its current level of 7.3 billion (Ray et al., 2013).

Yield growth has been examined for various crops at country, regional, and global levels using either aggregate or experimental data. The bulk of the empirical studies argue that crop yield growth has experienced declines or, at best, stagnation (Ladha et al., 2003; Pathak et al., 2003; Finger, 2010; Grassini et al., 2013; Ray et al., 2013; Iizumi et al., 2014b). Empirical analysis also suggests considerable heterogeneity in yield growth across crops and regions, with yield stagnation particularly pronounced in developing countries. Yield stagnation and collapse are also cited as contributors to the increased yield instability across a broad region of the Southern Hemisphere since the late 20th century (Iizumi et al., 2014a). The deceleration of yield growth has been linked to various factors, such as climate change, inadequate funding for research and development, intensification of production systems, increasing water scarcity, agricultural policies, and natural plateauing (Cassman, 1999; Rosegrant and Cline, 2003; Lobell and Field, 2007; Piesse and Thirtle, 2010; Lobell et al., 2011).

Despite the breadth and depth of the literature, there is no consensus on the nature and degree of yield growth slowdown, for at least two reasons. First, yield paths across commodities and regions could differ due to price changes of inputs and substitute commodities, policies, technical innovation, and consumer preferences *(xx-xx)*. Secondly, various modeling frameworks have been used in the literature to estimate yield growth which, often give different results (e.g., Hafner, 2003; Finger, 2010; Ray et al., 2012). Our research complements the existing literature by addressing these two issues as follows. First, we introduce an aggregate global yield measure which includes all food commodities for which data exist, thus accounting for the heterogeneity of yield paths. Second, we estimate the growth of the global yield index based on various methodologies and then apply three tests in order to determine which specification fits the data best and also establish if (and when) a structural break might have occurred and, if so, in what direction.

Production and calorific content data for 25 major crops covering the 1961-2017 period are included in the analysis (Appendix S1). These crops combined account for roughly 85 percent of the world agricultural land area. We then generate a global calorific yield index, based on the caloric content, land area, and production of each crop. We consider statistical methods to determine whether the log-level or level-level model fits the data best (based on (Ermini and Hendry, 2008) and (Spanos et al., 2008)). Structural breaks are tested for the global calorie-based yield index, and piecewise linear regression models are estimated to determine whether yield growth has decelerated and stagnated in recent years.

Preliminary results show that, a level specification is preferred over a log-level model. Of the three tests considered, two favor the level-level model and one fail to produce evidence in favor of one model over the other. We proceed to regress the yield in level against a linear and a quadratic time trend, both of which are positive. When measured as annual contribution (as opposed to percent change), global yields have not decelerated, and in fact may have accelerated in recent years. Furthermore, several econometric methods all point to a structural break in the yield index in 2004, coincidently around the time the food price boom began. We find that for the piecewise regression model with the structural break, regardless of the log-level or the level-level model, yield growth has in fact accelerated since 2004. Our results support the conclusions reached by Nelson et al. (2018) that, on a calorie basis, there is sufficient food to feed the global population in 2050.

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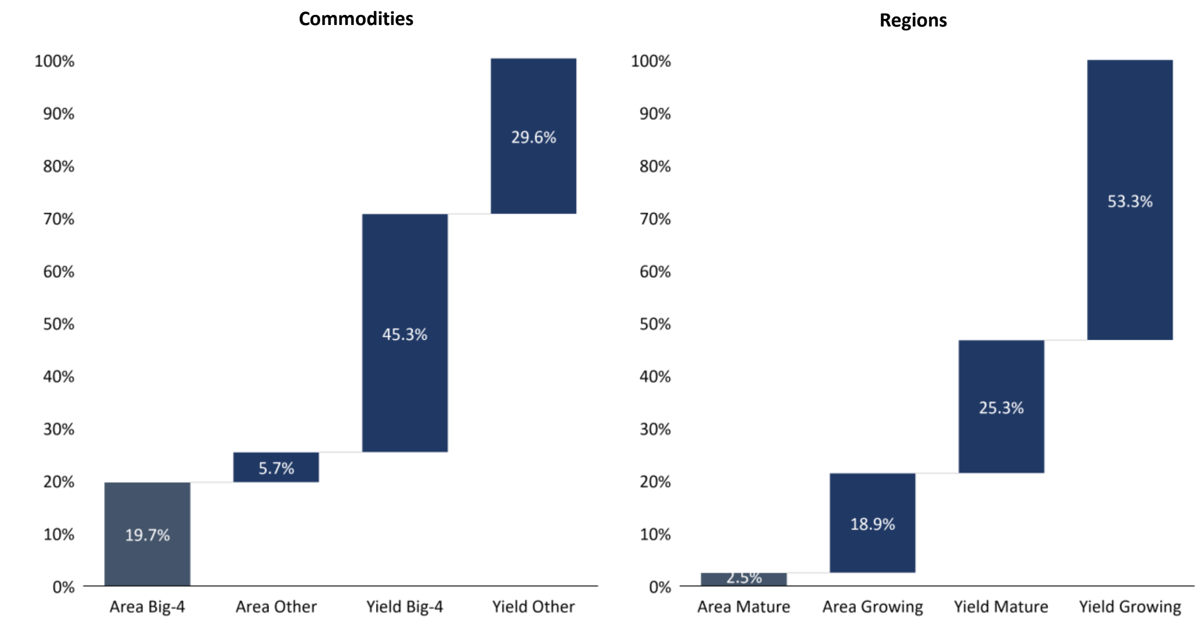
Table 1
Parameter estimates, global yield growth

	[1] $log(y_t)$	[2] y_t	[3] $log(y_t)$	[4] y_t	[5] $log(y_t)$	[6] y_t
β_0	8.48*** (0.01)	4,365.49*** (50.81)	8.41*** (0.01)	4,468.25*** (76.46)	8.42*** (0.01)	4,460.02*** (52.61)
Trend	0.016*** (0.00)	125.06*** (1.52)	0.023*** (0.00)	114.61*** (6.08)	0.021*** (0.00)	119.58*** (2.03)
$Trend^2$	—	—	-0.0001*** (0.00)	0.18** (1.87)	—	—
$(Trend - \tau) * D$	—	—	—	—	-0.0076*** (0.0007)	27.06*** (7.37)
DF-GLS	-1.56	-3.16*	-3.16**	-3.38**	-4.16***	-4.04***
PP	-3.36**	-5.31***	-5.16***	-5.62***	-6.09***	-6.42***
Adj-R^2	0.980	0.992	0.992	0.992	0.993	0.993

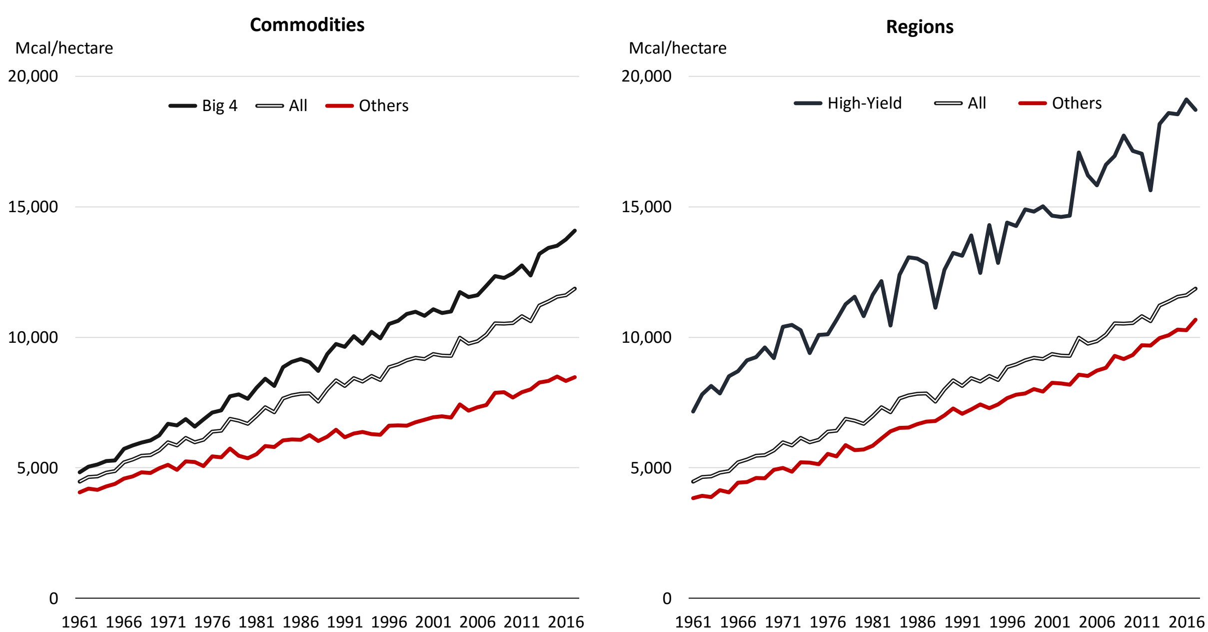
Notes: The top row denotes the dependent variable. *Standard errors* are reported in parenthesis. The break year for model (5) is 1987 ($\tau = 26$), and for model (6) it is 2002 ($\tau = 41$). DF-GLS and PP denote the Generalized Least Squares Dickey-Fuller and Phillips-Perron stationarity statistics. "—" implies that the respective trend was not included in the regression. One (*), two (**), and three (***) asterisks denote significance at 10, 5, and 1 percent levels.

Figure 1
Production growth decomposition



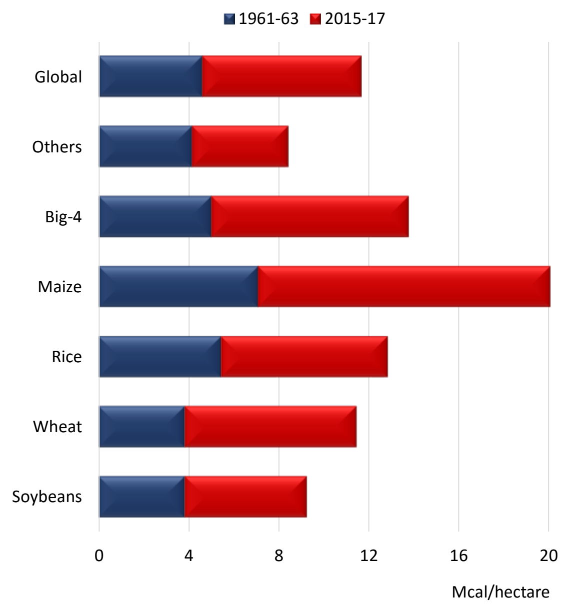
Source: Authors' calculations based on FAO data
Notes: Big 4 refers to the sum of maize, wheat, rice, and soybeans. Mature region includes Europe and North America.

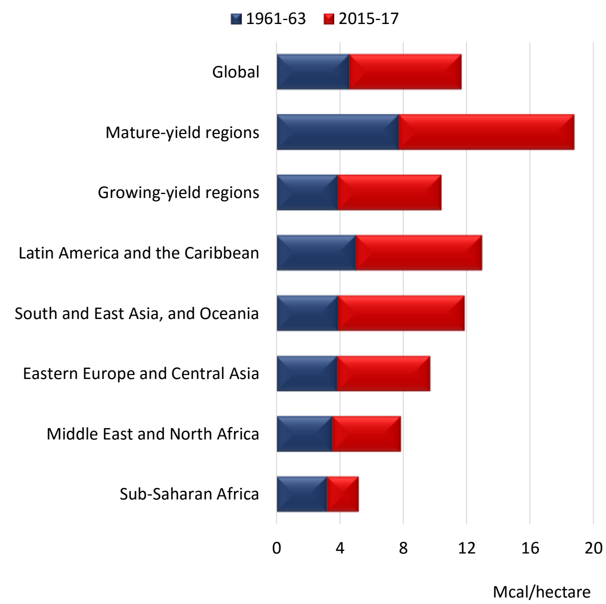
Figure 2
Global, commodity-specific, and regional yield indices



Source: Authors' calculations based on FAO data
Notes: Big 4 refers to the sum of maize, wheat, rice, and soybeans. High yield includes Europe and North America

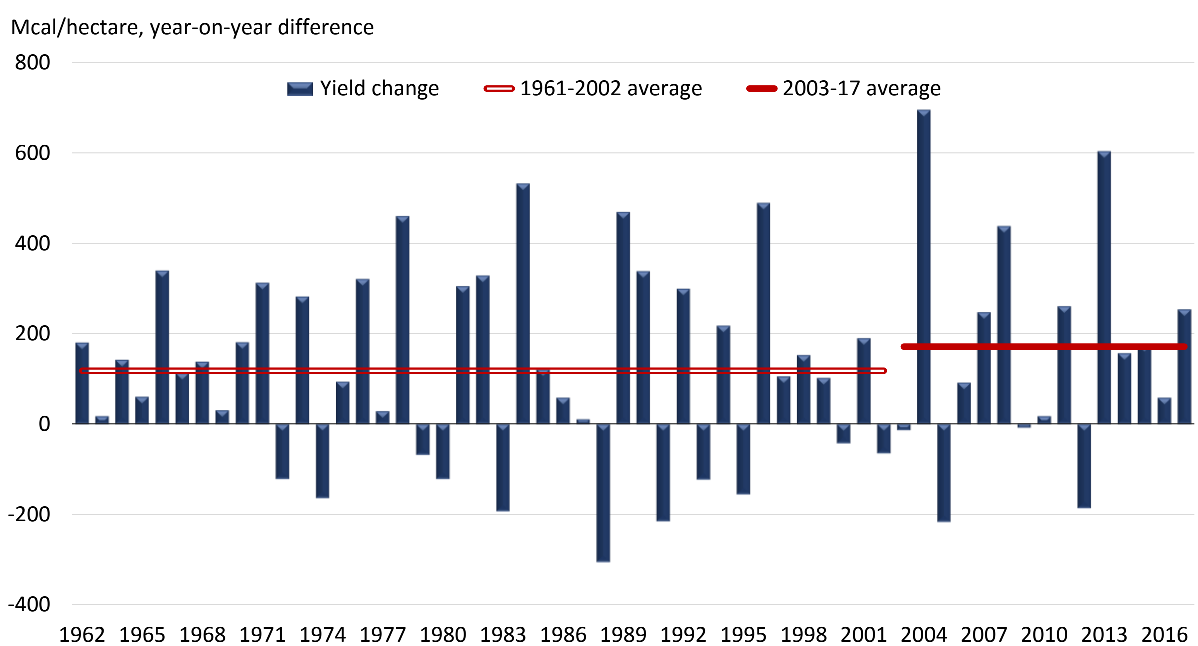
Figure 3
Commodity-specific and regional yield averages





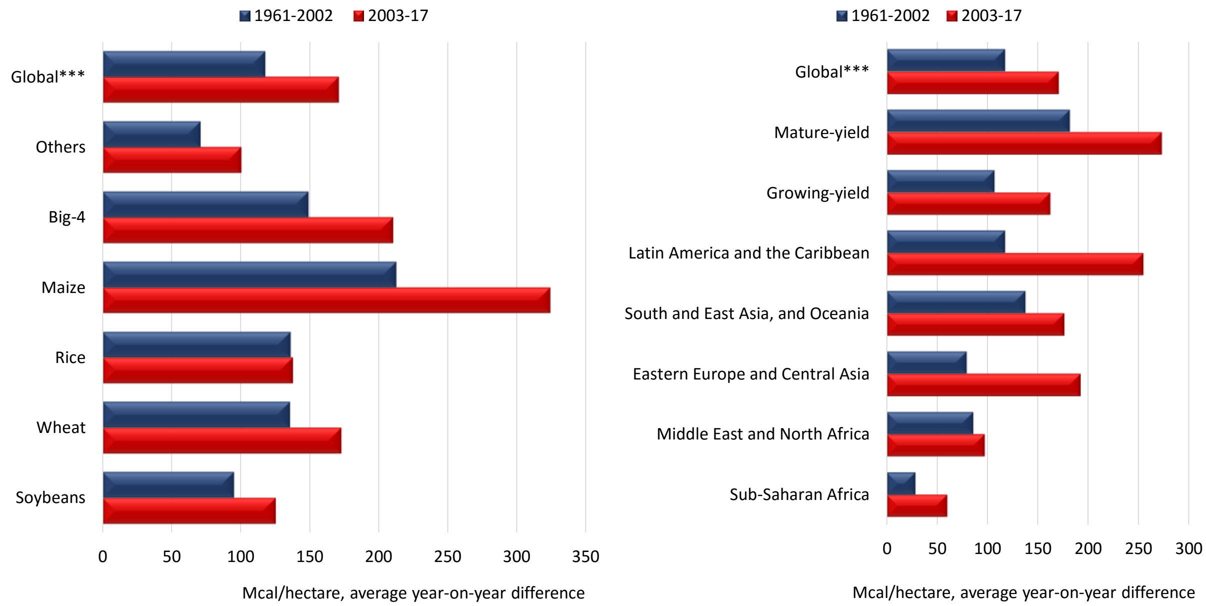
Source: Authors' calculations based on FAO data
Notes: The 2015-17 bar denotes incremental yield.

Figure 4
Global yield index



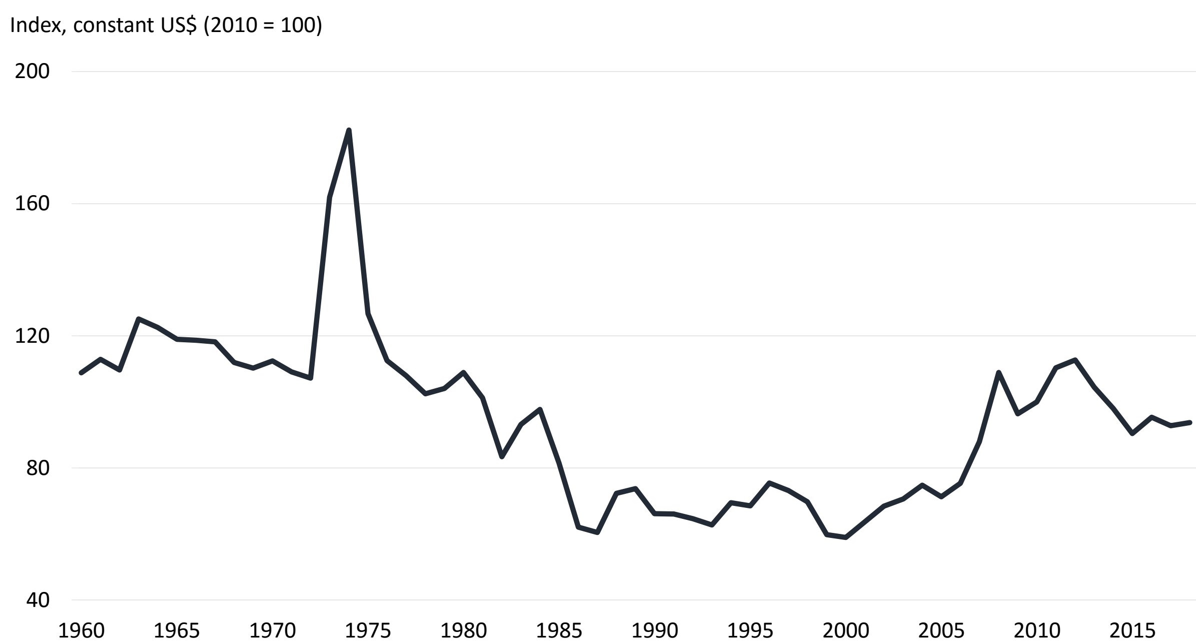
Source: Authors' calculations based on FAO data

Figure 5
Commodity-specific and regional yield indices



Source: Authors' calculations based on FAO data.
Notes: Asterisks denote significance of the structural break at the 10 (*), 5 (**), and 1 (***) percent.

Figure 6
Food price index



Source: World Bank

Appendix S1: Data description

Data on land areas and production are collected for 25 major agricultural commodities, including grains, oilseeds, fruits, fibers, and other crops for 1961-2017 from the Food and Agricultural Organization (FAO). Table S1 lists the commodities considered in the analysis, which combined account for approximately 85 percent of the global total agricultural land use during the sample period. The calorific information of each commodity is also obtained from the FAO, as reported in the Food Balance Sheets. Although many different data sources exist for commodity production as well as their nutritional values, there exists considerable variation in how these data are collected (e.g., dry vs raw weight). For consistency, we draw all data used in the analysis from FAO. In addition to the crop-level data, we also collect the regional-level data for each crop

Appendix S2: Model description

This appendix describes the conceptual framework behind the construction of the global yield index and the estimation of growth rates. The next section describes the construction of the yield index. The second section outlines the assumptions and implications of growth rate estimates based on exponential and linear regressions. The third section discusses ways of accounting for non-linearities, including squared time trend and structural breaks. The last section outlines the model selection procedure by utilizing the Box-Cox transformation and encompassing test along with stationarity statistics.

A global yield index

We compute the global calorie-based yield index as follows:

$$y_t = \frac{\sum_{i=1}^{N} w_i Q_{it}}{\sum_{i=1}^{N} L_{it}}, \tag{1}$$

where $i = 1, \ldots, N$ represents individual commodities, $t = 1, \ldots, T$ represents year, w_i is the calorific content of commodity i per weight unit, Q_{it} is the total output of commodity i at year t in weight unit, and L_{it} denotes land allocated to commodity i at year t. In addition to the global calorie-based yield index, sub-indices for groups of commodities as well as regions are computed. Calorific-based indices, while somewhat infrequent, they have been used in the past, including Williamson and Williamson (1942) for food consumption, Roberts and Schlenker (2009) for production and consumption of grains and oilseeds, Bobenrieth et al (2013) for global grain stocks, and Cassidy et al (2013) for the share of calories going for animal feed and biofuel production.

Estimating growth rates

The growth rate between period 1 and 2, denoted by ρ, typically reported as percent change, is calculated as follows:

$$\rho = (y_1 - y_0)/y_0, \tag{2}$$

where y_1 and y_0 denote yield in current and previous period. Equation (2) can also be written as $y_1 = (1+\rho)y_0$. Assuming that y_t grows at rate ρ in all periods, while in each period it is subjected to stochastic shocks η_t, it can be rewritten as:

$$y_t = (1+\rho)y_{t-1}\eta_t. \tag{3}$$

Taking a one-period lag in (3) gives $y_{t-1} = (1+\rho)y_{t-2}\eta_{t-1}$, which upon substitution back into (3) gives $y_t = (1+\rho)^2 y_{t-2}\eta_t\eta_{t-1}$. Backward substitution to period *0* gives:

$$y_t = (1+\rho)^t y_0 \eta_t \eta_{t-1} \ldots \eta_0 \tag{4}$$

Taking natural logarithms in (4) and setting $\beta_0 = log(y_0)$, $\beta_1 = log(1+\rho)$, and $\varepsilon_t = \sum_t log(\eta_t)$, results in the following expression:

$$log(y_t) = \beta_0 + \beta_1 t + \varepsilon_t, \qquad (5a)$$

Equation (5a) is a frequently used regression where the parameters β_0 and β_1 are estimated with ordinary least squares and the growth rate is calculated as $\rho = exp(\beta_1) - 1$. Often the growth rate is reported as the estimate of β_1 rather than ρ, since for small growth rates β_1 and ρ are approximately equal—at the limit $\beta_1 = \rho = 0$.

Estimating growth rates according to (5a) rests on the assumption that y_t must grow at a similar rate (in percent terms) throughout the sample period in order to render the error term white noise (i.e., making η_t log-normally distributed with mean equal to 1). However, while the proportionality assumption may be reasonable for short periods of time (e.g., a decade) and relatively small growth rates (e.g., below one percent), it may be unrealistic when long periods of time are considered such as 55-year sample in the current context. An alternative (and, perhaps, more realistic) assumption is that y_t grows by a constant amount in each period, say μ, in which case the relationship between current and previous period yield becomes $y_1 = \mu + y_0$ or, in the general case, $y_t = \mu + y_{t-1}$. Applying backward substitution similar to (3) gives $y_t = \mu t + y_0$. Letting $\beta_0 = y_0$ and $\beta_1 = \mu$, and appending an additive error term results in:

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t. \qquad (5b)$$

As before, (5b) is estimated with ordinary least squares.

Because the assumptions behind (5a) and (5b) are fundamentally different, the choice of the model has important implications, especially in assessing whether yield growth has decelerated. To see this, consider [wheat], the yields of which during 1960-65 grew by [xx] percent (in terms of (5a)) or by [xx] kgs (in terms of (5b)).

Note that equations (5a-b) could be estimated by taking the first differences:

$$\Delta log(y_t) = \beta_1 + \varepsilon_t, \qquad (6a)$$

$$\Delta y_t = \beta_1 + \varepsilon_t, \qquad (6b)$$

where Δ denotes the difference operator (e.g., $\Delta y_t = y_t - y_{t-1}$). Note that β_0 and t drop out of the equation because they take the value of zero and one, respectively. Equations (6a-b) are often referred to as a random walk with drift.

Accounting for non-linearities and structural breaks

Regardless of whether a logarithmic or linear model best approximates yield trends, both models rest on the assumption that growth is constant throughout the sample size. Because yield paths could be subjected to non-linearities—in response policies, changes in preferences, or technology-induced shocks—growth rates could accelerate decelerate either in a gradual manner or take sharp turns. There are two ways in which equations (5a-b) and (6a-b) can be amended to account for such non-linearities. First, a square time trend can be as follows:

$$ln(y_t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t, \tag{7a}$$

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t, \tag{7b}$$

where β_1 approximates the growth rate as before and β_2 gives the rate at which growth decelerates (when negative) or accelerates (when positive). More than one square trend could be included in (7a-b) to capture non-linearities in a more realistic manner, such as an S-shaped curve whereby yields initially grow at an accelerating rate before deceleration and eventual plateauing takes place. The S-curve hypothesis has been tested often in the context of the relationship between commodity consumption and income (see Tilton 1990; Cleveland and Ruth 1998).

A second way to account for non-linearities is to impose one or more structural breaks and estimate separate growth rates for each subperiod. In the case of one structural break, the regressions take the following form:

$$log(y_t) = \beta_0 + D + \beta_1 tD + \beta_2 t(1 - D) + \varepsilon_t, \tag{8a}$$

$$y_t = \beta_0 + D + \beta_1 tD + \beta_2 t(1 - D) + \varepsilon_t, \tag{8a}$$

where D takes the value of 1 up to year τ and zero elsewhere. If τ is unknown, it can be determined by the QLR procedure, originally proposed by Quandt (1960) and later expanded by Andrews (1993) and Andrews and Ploberger (1994). The QLR test is defined as the largest Chow F-statistic, $F_T(\tau)$, allowing τ to vary during the entire sample as follows:

$$QLR_T = \max_{\tau_1 \le \tau \le \tau_2} F_T(\tau), \tag{9}$$

where τ_1 and τ_2 denote the sub-samples before and after the structural break. For improved performance Andrews (1993) suggested trimming the sample by 15 percent on each end. If a structural break is found, a piecewise model can be utilized to ensure continuity at τ (Poirier 1976, Boyce 1986, Baffes and Vallee 2003), in which case (8a-b) become:

$$log(y_t) = \beta_0 + \beta_1 t + \beta_2 (t - \tilde{\tau})D + \varepsilon_t, \tag{10a}$$

$$y_t = \beta_0 + \beta_1 t + \beta_2 (t - \tilde{\tau})D + \varepsilon_t, \tag{10b}$$

where $\tilde{\tau}$ denotes the QLR-based estimate of τ. Structural break(s) can be applied to (7a-b) as well; however, the simultaneous estimation of structural breaks and several t^2 terms can cause overparameterization and difficulties in interpreting the results. More importantly, because of the different assumptions of modeling growth rates, the nature and degree of non-linearities should be interpreted differently, depending on which model chosen. Thus, selection of the appropriate model should be based on a carefully selected testing procedure, which is the subject of the next section.

Appendix S3: Key statistics

Table S3.1
Decomposition of area, yield, and production growth by main crop

	Maize	Wheat	Rice	Soybeans	Big-4	Other	ALL
A. 1961-63 average							
Area (million hectares)	105.8	206.0	118.3	24.0	454.1	397.9	852.0
Yield (Mcal/ha)	7.1	3.8	5.4	3.8	5.0	4.1	4.6
Production (billion Mcal)	747.8	786.0	643.3	91.8	2,268.9	1,645.5	3,914.3
Area (share)	12.4	24.2	13.9	2.8	53.3	46.7	100
Production (share)	19.1	20.1	16.4	2.3	58.0	42.0	100
B. 2015-17 average							
Area (million hectares)	194.3	220.9	164.9	122.1	702.2	456.2	1,158.4
Yield (Mcal/ha)	20.1	11.5	12.9	9.2	13.8	8.4	11.7
Production (billion Mcal)	3,900.7	2,530.2	2,119.7	1,129.3	9,679.9	3,846.5	13,526.4
Area (share)	16.8	19.1	14.2	10.5	60.6	39.4	100
Production (share)	28.8	18.7	15.7	8.3	71.6	28.4	100
C. Growth from 1961-63 to 2015-17 (percent, log change)							
Area	60.8	7.0	33.2	162.6	43.6	13.7	30.7
Yield	104.4	110.0	86.1	88.4	101.5	71.3	93.3
Production	165.2	116.9	119.2	251.0	145.1	84.9	124.0
D. Contribution to growth from 1961-63 to 2015-17 (share)							
Area	36.8	6.0	27.9	64.8	30.0	16.1	24.8
Yield	63.2	94.1	72.2	35.2	70.0	83.9	75.2
Production	100	100	100	100	100	100	100
E. Contribution to growth from 1961-63 to 2015-17 (production-adjusted share)							
Area	8.8	1.2	4.5	3.5	19.5	5.7	24.8
Yield	15.2	18.2	11.6	1.9	45.3	29.6	75.2
Production	24.0	19.4	16.0	5.3	64.8	35.2	100

Notes: The changes from 1961-63 to 2015-17 have been calculated as logarithmic changes. The contribution of growth in the lower panel has been evaluated at the average production shares of the two sub-periods (i.e., the contribution of maize area has been calculated as follows: 8.8 = 0.24*36.8, where 0.24 = 0.5*(0.191 + 0.288). Some numbers may not add up exactly due to rounding.

Source: Authors calculations based on FAO data.

Table S3.2
Decomposition of area, yield, and production growth by broad region

	ECA	SEA	SSA	MENA	LAC	Low-Y	High-Y	ALL
A. 1961-63 average								
Area (million hectares)	170.1	358.6	69.6	35.4	58.8	692.5	159.5	852.0
Yield (Mcal/ha)	3.8	3.9	3.2	3.5	5.0	3.9	7.7	4.6
Production (billion Mcal)	650.5	1,393.3	222.6	125.0	294.7	2,686.1	1,228.2	3,914.3
Area (share, %)	20.0	42.1	8.2	4.2	6.9	81.3	18.7	100
Production (share, %)	16.7	35.6	5.7	3.2	7.5	68.6	31.4	100
B. 2015-17 average								
Area (million hectares)	130.5	494.5	169.8	45.5	143.7	984.0	174.4	1,158.4
Yield (Mcal/ha)	9.7	11.9	5.2	7.9	13.0	10.4	18.8	11.7
Production (billion Mcal)	1,267.3	5,873.5	883.7	357.0	1,866.9	10,248.4	3,278.0	13,526.4
Area (share, %)	11.3	42.7	14.7	3.9	12.4	84.9	15.1	100
Production (share, %)	9.4	43.4	6.5	2.6	13.8	75.8	24.2	100
C. Growth from 1961-63 to 2015-17 (percent, log change)								
Area (%)	-26.5	32.1	89.2	25.1	89.3	35.1	8.9	30.7
Yield (%)	93.0	111.8	48.7	80.3	95.2	98.8	89.2	93.3
Production (%)	66.7	143.9	137.9	104.9	184.6	133.9	98.2	124.0
D. Contribution to growth from 1961-63 to 2015-17 (share)								
Area (%)	-39.7	22.3	64.7	24.0	48.4	26.2	9.1	24.8
Yield (%)	139.5	77.7	35.3	76.5	51.6	73.8	90.9	75.2
Production (%)	100	100	100	100	100	100	100	100
E. Contribution to growth from 1961-63 to 2015-17 (production-adjusted share)								
Area (%)	-5.2	8.8	4.0	0.7	5.2	18.9	2.5	24.8
Yield (%)	18.1	30.7	2.2	2.2	5.5	53.3	25.3	75.2
Production (%)	13.0	39.5	6.1	2.9	10.7	72.2	27.8	100

Notes: See notes in Table 3.1. Areas include: Eastern Europe and Central Asia (ECA); South and East Asia, and Oceania (SEA); Sub-Saharan Africa (SSA); Middle East and North Africa (MENA); and Latin America and the Caribbean (LAC). Low-Y denotes the regional sum. High-Y includes North America, Northern Europe, Western Europe, and Southern Europe.

Source: Authors calculations based on FAO data.

Appendix S4: Parameter estimates for various sub-indices

Table S4.1
Parameter estimates of the base models

	Grains	Oilseeds	Big 4	Other	Aggregate	Grains	Oilseeds	Big 4	Other	Aggregate
	Model [1]: $log(y_t) = \beta_0 + \beta_1 t + \varepsilon_t$					Model [2]: $y_t = \beta_0 + \beta_1 t + \varepsilon_t$				
β_0	8.492***	8.040***	8.57***	8.365***	8.479***	4269.057***	2580.927***	4702.35***	4079.703***	4365.487***
	(0.011)	(0.006)	(0.013)	(0.008)	(0.010)	(69.793)	(70.017)	(60.83)	(49.130)	(50.810)
Trend	0.018***	0.019***	0.018***	0.012***	0.016***	151.127***	108.882***	157.54***	73.675***	125.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(2.093)	(2.100)	(1.82)	(1.474)	(1.524)
Adj-R^2	0.981	0.995	0.974	0.976	0.980	0.989	0.980	0.993	0.978	0.992
DF-GLS	-1.68	-3.99***	-1.27	-1.92	-1.56	-2.57	-0.75	-3.63**	-2.74	-3.16*
PP	-3.67***	-7.86***	-2.84*	-4.32***	-3.36**	-4.55***	-2.36	-5.86***	-4.11***	-5.31***
	Model [3]: $log(y_t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$					Model [4]: $y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$				
β_0	8.420***	8.029***	8.476***	8.338***	8.411***	4523.27***	3107.70***	4688.42***	4212.42***	4468.25***
	(0.012)	(0.010)	(0.011)	(0.012)	(0.010)	(97.93)	(53.00)	(94.12)	(72.22)	(76.46)
Trend	0.026***	0.021***	0.028***	0.015***	0.023***	125.27***	55.31***	158.96***	60.18***	114.61***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(7.79)	(4.22)	(7.49)	(5.75)	(6.08)
$Trend^2$	-0.0001***	-0.0000	-0.0002***	-0.0000***	-0.0001***	0.45***	0.92***	-0.02	0.23**	0.18*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.13)	(0.07)	(0.12)	(0.10)	(0.10)
Adj-R^2	0.991	0.995	0.993	0.979	0.991	0.991	0.995	0.992	0.980	0.992
DF-GLS	-3.11*	-4.25***	-3.41**	-2.95*	-3.16*	-3.22**	-4.61***	-3.63**	-2.96*	-3.38**
PP	-5.28***	-8.20***	-5.43***	-4.48***	-5.16***	-5.48***	-7.74	-5.86***	-4.60***	-5.62***

Notes: The top row denotes the dependent variable of the sub-index. "Big 4" denotes the sum of maize, wheat, rice, and soybeans. "Other" refers to all other crops except for the big 4. "Aggregate" the sum of all crops reported in Table 2. Standard errors are reported in parenthesis. DF-GLS and PP denote the Generalized Least Squares Dickey-Fuller and Phillips-Perron stationarity statistics. One (*), two (**), and three (***) asterisks denote significance at 10, 5, and 1 percent levels.

Table xx
Parameter estimates, global yield growth

	β_0	*Trend*	*DF-GLS*	*PP*	*Adj-R^2*
$log(y_t)$	8.48*** (0.01)	0.016*** (0.00)	-1.56	-3.36**	0.980
y_t	4,365.49*** (50.81)	125.06*** (1.52)	-3.16*	-5.31***	0.992

Notes: The first column denotes the dependent variable. *Standard errors* are reported in parenthesis. DF-GLS and PP denote the Generalized Least Squares Dickey-Fuller and Phillips-Perron stationarity statistics. One (*), two (**), and three (***) asterisks denote significance at 10, 5, and 1 percent levels.