

Evaluation of Nigerian agricultural production data

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Abstract

The absence of an agricultural census in Nigeria means that samples for surveys to estimate agricultural production are obtained from a non-comprehensive, non-representative set of farms. Therefore, aggregate production data quality is questioned. The methods employed herein provide a new way to empirically evaluate the quality of agricultural production estimates. Two objective types of data, namely the normalised difference vegetation index (NDVI), a satellite remote-sensing measure of intertemporal vegetation changes, and prices, which reveal supply-use dynamics, are used to analyse the degree to which agricultural production estimates reflect adjustments in growing/market conditions. Broadly weak relationships were found between the production estimates and these objective measures, but with variations in degree across states. In addition, these two objective measures are more strongly related to each other than either is to production data. The results imply that the inclusion of NDVI and prices in agricultural production estimation models would improve the quality of the Nigerian production estimate.

Key words: agricultural production; data quality; satellite remote sensing; NDVI; agricultural prices

1. Introduction

The failure to collect data on the performance of economically important sectors in most African countries was highlighted by McMillan (2016) as a clear indicator of poor institutional development. Nigeria, a country with the largest economy in Africa (IMF 2016), is no exception, especially with its agricultural sector, which accounts for an estimated 20% of GDP (World Bank 2014) and an even larger share of employment (IMF 2016). Discrepancies across sources in reported agricultural statistics in Nigeria, called to attention by Jerven (2013) and also identified by Berry (1984) and Collier (1988), remain today (AMIS-FAO 2014).

An agricultural census establishes benchmarks for key variables such as agricultural production that remain reference points for other estimates until the next census (FAO 2015). However, Nigeria has not had a census in four decades (Onyeri 2011), so survey samples are not drawn from a representative set of farms (David 1998). This calls into question the quality of the data aggregated from such samples.

In this paper we provide a new way of evaluating the quality of agricultural production estimates, with Nigeria as a case study. Two types of objective information, namely the normalised difference vegetation index (NDVI), a satellite remote-sensed measure of changes in vegetation “greenness” over time (Peters *et al.* 2002), and prices, which reflect supply-use dynamics (Sahn & Delgado 1989), were used to analyse the degree to which production estimates are consistent with changes in growing/market conditions. Correlations were estimated between state-level production estimates and these objective measures. Implications for the national estimates are discussed, and the inferences are supplemented with a set of national estimate evaluation results.

2. Overview of the Nigerian agricultural statistics system

Multiple state, national and international sources gather and report agricultural production estimates for Nigeria. It is commonplace for these sources to share information, since only a few entities implement surveys. However, these surveys often are implemented irregularly and are not plausibly comprehensive nor representative.

The Federal Ministry of Agriculture and Rural Development (FMARD) has the legislative mandate for agricultural statistics (Onyeri 2011) and does so largely through the dissemination of the “Agricultural Production Survey” reports of the National Programme for Agriculture and Food Security (NPAFS). The data in these reports are provided directly by state-level agricultural development projects (ADP) and other institutions of the state ministry of agriculture, which undertake their own farm surveys (NPAFS 2010). The FMARD also disseminates agricultural performance reports produced by the National Agricultural Extension and Research Liaison Service (NAERLS) in co-operation with Ahmadu Bello University and other national government ministries, which vary over time. While these reports have been disseminated for over 20 years, they now appear less frequently and are only presently online for 2009 to 2013¹ (AMIS-FAO 2014).

The Nigerian National Bureau of Statistics (NBS n.d.) also reports agricultural statistics, partly based on ADP estimates. Its data are for a longer time series and are more accessible online than those of NPAFS and NAERLS.² From 1994 to 2003, NBS relied solely on data from the ADP and the state ministry of agriculture (Okoukoni 2007). NBS then implemented a survey over the period 2004 to 2006 in collaboration with the Central Bank of Nigeria (CBN) and the Nigerian Communications Commission (NCC) (Okoukoni 2007), and again from 2010 to 2011 with unknown collaborators (CountrySTAT-Nigeria 2016). By implication, NBS data for 2007 to 2009 and for 2012 are either forecasts based on data from these surveys, and/or compilations of ADP and state ministry of agriculture data.

NBS agricultural statistics currently are available on the CountrySTAT (2013) website for Nigeria, a donor-funded effort administered by the FAO Statistics Division. The metadata documents on CountrySTAT,³ however, do not allow for clear determination of the origin of data that are not from the survey year. While both the NBS data portal and CountrySTAT websites have the same agricultural estimates through 2006, the CountrySTAT (2013) website provides estimates through 2012 with some associated metadata documentation.⁴

¹ There is also a 2006 report on the NAERLS website (<http://www.naerls.gov.ng/site2/>), but this only includes relatively sparse descriptions of percentage increases (no decreases) of crop area planted and production, rather than raw data.

² NBS data are available on both the NBS data portal (<http://nigeria.opendataforafrica.org/>) and the Nigeria CountrySTAT website (<http://www.countrystat.org/home.aspx?c=NGA>).

³ Some of the metadata documents on the CountrySTAT Nigeria website are the same as those obtained directly from NBS during field work.

⁴ NBS data downloaded from the NBS data portal website in 2014 were for 1994 to 2005. These were subsequently downloaded in 2015, but for 1995 to 2006. Those downloaded in 2016 are the same values as downloaded in 2014, but all shifted up one year. No explanation is provided for this adjustment.

NPAFS, NAERLS and NBS, and the state ministry agencies from which they commonly obtain data, each reports individual state agricultural production estimates. National production estimates are obtained through summation of the individual state estimates, and their reliability therefore is inherently dependent on the quality of the individual state estimates. The Central Bank of Nigeria (CBN) also reports agricultural production in its annual reports (e.g. CBN 2012). Only national production estimates are reported, but these appear to be unreliable.

Numerous international sources report national production estimates for Nigeria. The USDA and the FAO are the most important. The USDA reports estimates through its Production, Supply, and Distribution (USDA-PSD n.d.) online database. The FAO does so through both its FAOSTAT (2015a) database and its Agricultural Market Information System (AMIS-FAO 2011) database, a G-20 initiative (G-20 2011).⁵

Staff of the USDA and FAO co-ordinate with domestic government statistical agencies and other stakeholders to obtain their estimates (Paulino & Tseng 1980; Vogel & Bange 1999). Both sources use non-farm survey information to derive estimates and forecasts (Paulino & Tseng 1980). USDA-PSD estimates also use remote sensing information, such as satellite imagery (Vogel & Bange 1999; Becker-Reshef *et al.* 2010). It is unclear whether Nigerian national government sources use non-survey (e.g. weather) information to form their production estimates. NAERLS reports include rainfall data for some years, but it is unclear from the reports if and/or how these rainfall data are used.

Another international source is the Famine Early Warning Systems Network (FEWS-NET) of USAID. Rather than provide official production estimates, FEWS-NET releases annual “Food Security Outlook” reports and intra-annual updates, which include remote-sensed and ground-based weather information and price data. These are combined to describe changes in food commodity market conditions with a focus on identifying production shortfalls (FEWS-NET 2016b).

2.1 Current national production estimates

Plots from national and international sources for 2000 to 2013 are provided for five key food security crops: cowpeas, maize, millet, rice and sorghum, to show how the estimates have varied over time. Figure 1 includes plots of rice and maize production estimates. The CBN (and NPAFS to a lesser degree) estimates simply follow a steady upward trend from a base estimate; they obviously do not reflect vegetation fluctuations over time. Aside from the outlier estimates of CBN, estimates among the other sources move together for much of the earlier period, but then diverge.

⁵ Although both entities are hosted at the FAO, FAOSTAT and AMIS differ in their methods of provision of estimates. For example, AMIS estimates are reported on a crop year basis (AMIS-FAO 2016), while those by FAOSTAT are by calendar year (FAOSTAT 2015b).

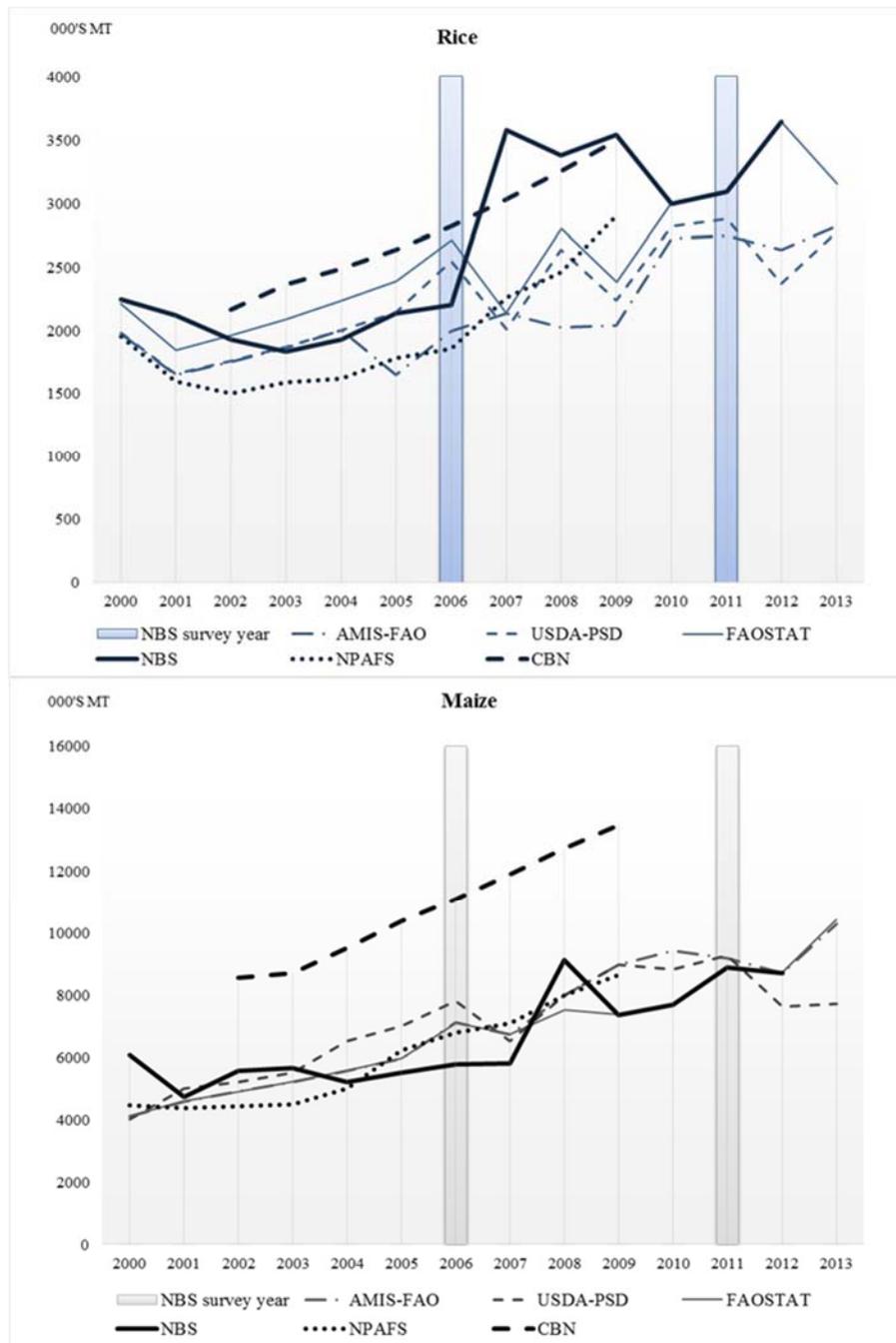


Figure 1: Nigerian rice and maize production estimates across sources for the period 2000 to 2013

Figure 2 includes plots of millet and sorghum production estimates. CBN estimates again show an uninterrupted upward trend, while the international sources move independently from national sources. USDA-PSD estimates for millet converge to the NBS and NPAFS estimates around 2005, but then diverge by 2012 and 2013. Both USDA-PSD and FAOSTAT sorghum estimates converge toward the NBS and NPAFS estimates around 2009, and have followed them since then.

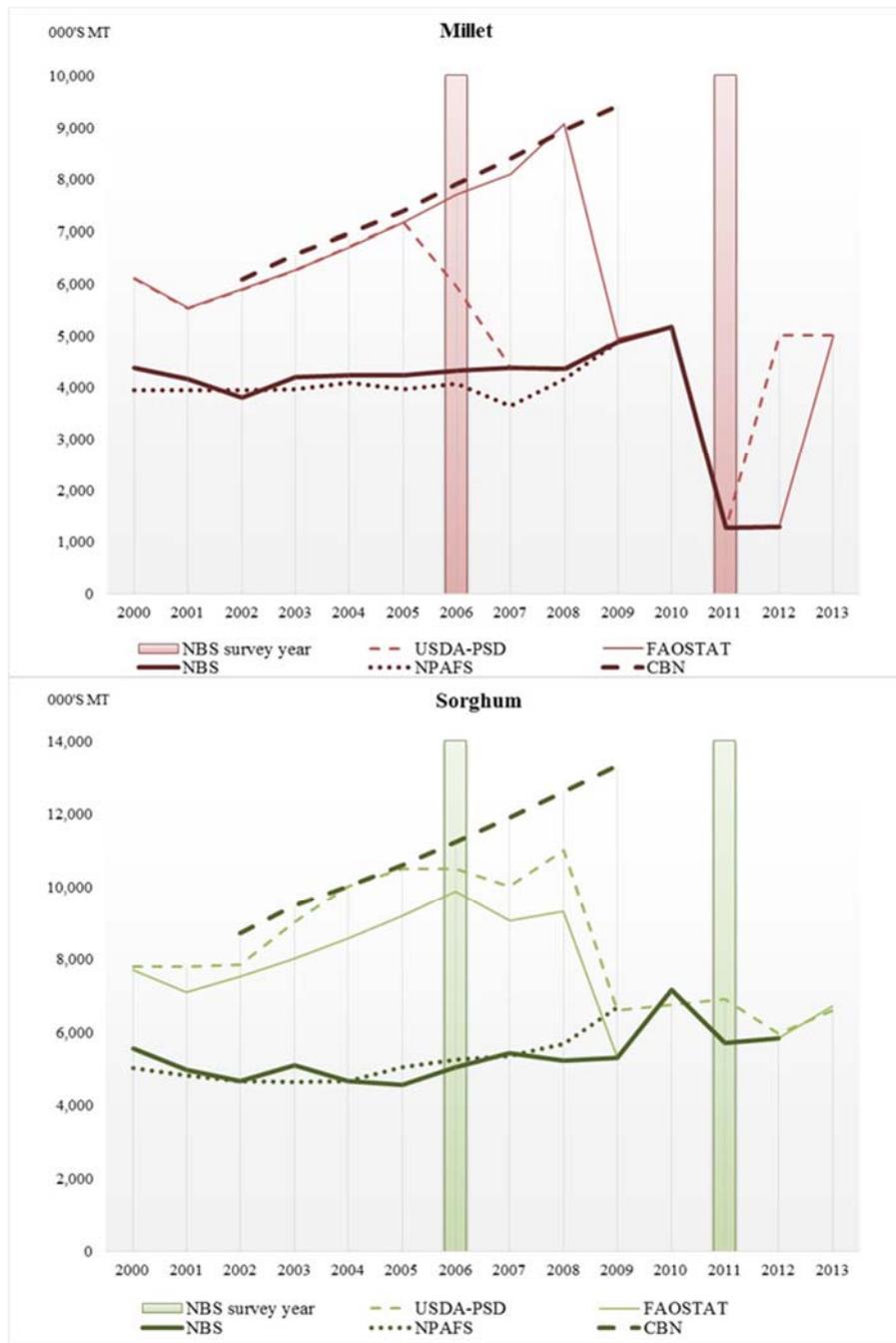


Figure 2: Nigerian millet and sorghum production estimates across sources for the period 2000 to 2013

Figure 3 includes a plot of cowpea production estimates over time. The FAOSTAT estimates were substantially higher than those of NBS and NPAFS for much of the observation period, but then converged with the NBS value by 2009. However, the FAOSTAT estimate for 2013 is less than 60% of the magnitude of that for 2012.⁶ There is much volatility in the NBS cowpea estimates from 2009 to 2012. The CBN estimates are again distinct outliers.

⁶ Berry (1984) described even larger fluctuations in agricultural production that resulted from the implementation of surveys by the Nigerian Federal Office of Statistics (the predecessor to NBS) in the 1960s. The estimates obtained from surveys were a meagre 10% of the average level of the estimates from years prior to the survey (Berry 1984).

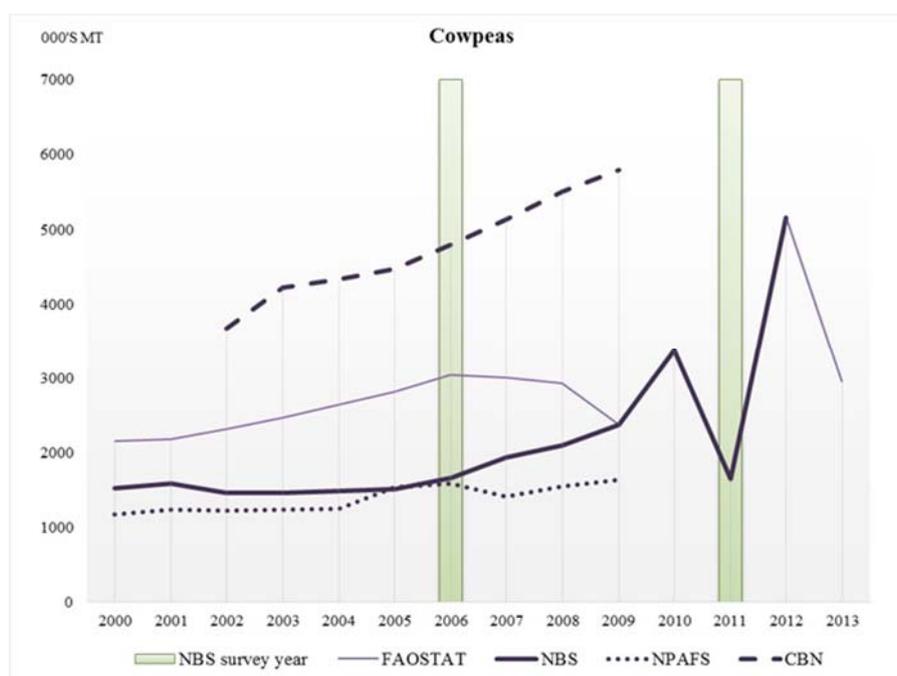


Figure 3: Nigerian cowpea production estimates across sources for the period 2000 to 2013

2.2 Statistical rebasing and revisions

Statistical rebasing, defined by the FAO Statistics Division as the adjustment to sampling weights (GSARS 2016), appears to apply for production estimates for some crops and some years following the implementation of the NBS survey, especially from 2010 to 2011. Rebasing of estimates upon implementation of the 2010/2011 NBS survey is observed to have occurred for all analysed crops except sorghum. However, the volatility of the NBS production estimates for cowpeas from 2009 to 2012 makes it difficult to ascertain whether a stable, rebased estimate exists at all. The rebasing of NBS millet estimates is most problematic because of the failure to revise prior estimates after the stark adjustment to the 2011 levels (which remained the same for 2012). While this failure is most applicable to the NBS millet estimates, the observed “regime change” during which international sources converged toward the NBS estimates for all crops around 2009 reflects a similarly stark adjustment in estimate levels without subsequent revision for non-NBS survey years. The inconsistency in method for the determination of estimates in non-survey years leads to much confusion with regard to the accuracy of both the levels of estimates and intertemporal variation in the data. These observations make the use of “historical” time series data in empirical analyses pointless.

3. Evaluation methods

The empirical analysis that follows provides insights into the quality of these current estimates of agricultural production levels in Nigeria. Cross-source co-ordination was measured first, such that the correlation between agricultural production estimates and NDVI measures, production estimates and prices, and NDVI and prices was calculated sequentially, and then the results were compared. If the production estimates are not correlated with the NDVI measures or prices, they do not reflect intertemporal fluctuations in growing/market conditions, while if they correspond well, then market prices and vegetation vary systematically. It follows then that, if production estimates are not correlated with either of these variables, the estimates are more reflective of poor sampling and/or aggregation methodologies than actual agricultural production.

The empirical analysis focuses on the agricultural production estimates for Borno, Kano and Niger states, for the same crops as above.⁷ Implications for the national estimates are discussed, and the inferences obtained are supported with some national-level results.

4. Relationships between agricultural production, NDVI and prices

Theoretical and empirical relationships between agricultural production, NDVI and prices can be found in the literature on remote sensing and economics. While expectations for the strength of the relationships of these variables can be formed based on previous findings, measurement is complicated by the way in which these data are typically gathered. The complications in data construction are particularly applicable in the Nigerian case.

4.1 Agricultural production and NDVI

The correlation between NDVI and agricultural production estimates is calculated in order to analyse how well production estimates reflect changes in growing conditions over time. We are unaware of any published studies that have estimated the relationship between NDVI and yield in Nigeria, and none are listed in the comprehensive review articles by Huang and Han (2014) and Funk and Budde (2009). Nonetheless, we expect that the positive relationship between agricultural vegetation and NDVI found by Maselli *et al.* (2000) and Rasmussen (1992) in the Sahelian region of West Africa will apply broadly to Northern Nigeria, our region of focus.

However, it is likely that there will be some variation in the degree of correlation between NDVI and yield across the analysed states and crops. In the meta-analysis by Huang and Han (2014), they found a lower estimated correlation between these variables in humid subtropical regions relative to semi-arid ones. This means that, across all crops, the correlation between NDVI and yield may be lower in Niger State, which is in the North Central region, than in Kano and Borno states, which are further north and closer to the Sahel. With regard to differences across crops, Huang and Han (2014) also found higher correlations among crops with larger rather than smaller leaf blade areas. Thus, it is expected that rice yield would have a somewhat lower correlation with NDVI than cowpeas, maize, millet or sorghum.

Because NDVI data are typically reported at 16-day and monthly intervals (NASA NEO n.d.) and production data typically on an annual basis, measuring the strength of the relationship is challenging. Huang and Han (2014) and Funk and Budde (2009) show that users of NDVI data often have different rules for the selection of time intervals to measure the correspondence with vegetation. Some researchers use average measures over specific periods (e.g. growing season), while others choose measures at particular points in time.

In this analysis, two time intervals were identified from studies in the remote sensing literature that appear to have the empirically strongest relationships with agricultural production, namely average growing season NDVI (Rojas 2007), and value associated with the month for the peak NDVI measure (Hochheim & Barber 1998). Results in Rasmussen (1992) showed that the inclusion of NDVI values that were closer to harvest and later than peak NDVI led to a higher correlation between yield and NDVI, which implies that the growing season average may be a better measure. Both time interval measures are used here and compared to discern if this is the case.⁸

⁷ See Hatzenbuehler (2016) for an extended analysis that also includes Oyo State for the cross-source correlation calculation.

⁸ In the empirical results section, the average NDVI value of the growing season is abbreviated as “GS”, and the value of month associated with the peak NDVI measure is referred to as “Peak”.

4.2 Agricultural production/NDVI and prices

In the “anticipatory price formation” agricultural market model of Working (1958), current market transactions, and thus prices, are dependent on expectations of future production and demand. In this framework, a large (small) expected harvest leads to lower (higher) prices (Working 1958; Sahn & Delgado 1989). The same relationship would apply for prices and NDVI, since NDVI captures fluctuations in growing conditions over time and is thus a plausible proxy for agricultural production (Brown & Kshirsagar 2015). Working (1958) found the strongest relationships between production estimates and harvest month prices, so the harvest months that correspond to Nigerian markets are used in this analysis. The FEWS-NET seasonal calendar shows that, in normal crop years, most of the crops in Southern Nigeria are harvested by November and in Northern Nigeria by December (FEWS-NET 2016a). So prices for the months of September, October and November were used and the results were compared.

While there is strong theoretical and empirical support for the relationship between production and prices, prices in markets that are not completely isolated are determined by both production within nearby regions and interregional trade opportunities (Ravallion 1986). Thus, the degree to which production (with NDVI now used as a proxy) explains price variation varies under different circumstances and crops. Previous work by Hatzenbuehler *et al.* (2017) on price transmission in Nigerian markets found that prices in commercial hubs like Kano are largely determined by intermarket trade, while in some rural markets there is a long lag in price transmission. The implication is that isolated, rural market prices are influenced relatively more by changes in local growing conditions, and hence production/NDVI, than are those in highly connected markets, especially for crops grown nearby. There is also higher rice price correlation across urban markets in Nigeria relative to that of other crops (Hatzenbuehler *et al.* 2017). This means that the relationships between rice prices and production/NDVI associated with a specific area are expected to be lower than those for cowpeas, maize, millet and sorghum.

With regard to spatial aspects, NDVI measures were averaged across the area within state borders. This was done because both the production estimates and prices used in the empirical analysis are state-wide aggregates.

While using a single spatial area makes comparisons for variable relationships across states somewhat clearer, the complication remains that the strength of estimated relationships between prices and production/NDVI will vary based on “local” conditions. We are able to test the conjecture of different variable relationship correspondence for states with varying market structures through the inclusion of a diverse set of states. For example, Kano State, home to Dawanau Market, one of the largest food commodity markets in West Africa (Terpend 2006), will plausibly have market interconnections that extend over a larger area than Niger State, which does not have as large a commercial hub. Thus, the effects of production on prices are expected to be more pronounced in Niger State than in Kano State, since “local” production comprises a larger relative share of overall supply. These complexities, and the nature of the data as state-wide averages rather than prices at local markets, lead to some noisiness in our results.

It is worthwhile noting that relatively limited local, non-aggregated market prices are available for Nigerian markets, especially in rural areas. Also, even though aggregated rural prices would be expected to have stronger relationships with production/NDVI than aggregated urban prices, aggregated rural prices currently are available for only four years (relative to the 10 years for urban prices). Thus, Nigerian food markets are currently relatively information poor with regard to both quantity and price data.

5. Data used

Production data were obtained from state government ADPs, NBS and NPAFS.⁹ Figure 4 below is a map that highlights Niger and Kano¹⁰ states, from which ADP data were obtained, as well as Borno State, the other state included in the analysis but for which ADP data were not gathered. The state-level production estimates are annual observations. All production data are for the period 2001 to 2009, except for the Kano State ADP series, which starts in 2002.

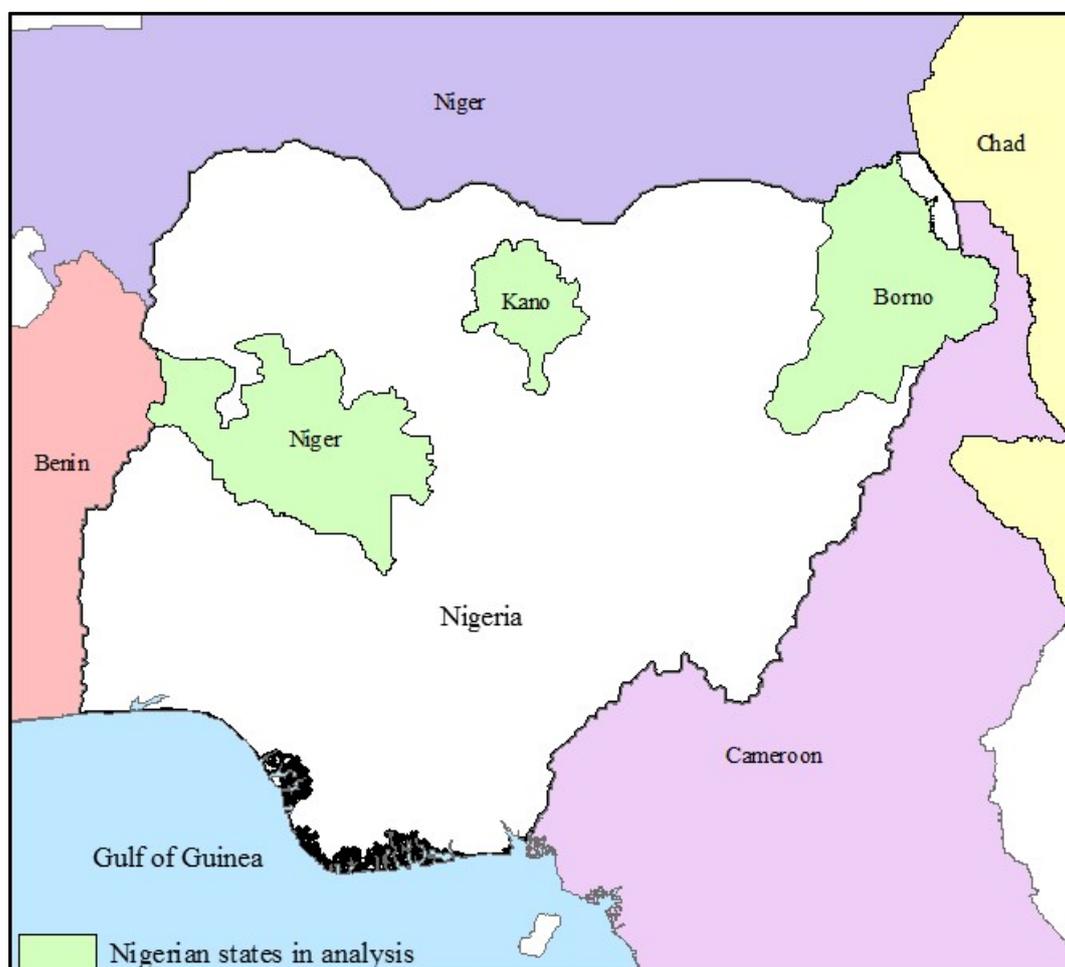


Figure 4: Map of states included in empirical analysis

Note: Figure produced by the authors with data from DIVA-GIS (n.d.) and Natural Earth Data (2015)

NDVI measures¹¹ were extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) photos taken intermittently by NASA satellites. These data were projected onto a global map, and an NDVI measure was obtained for a chosen land area through the application of a georeferenced “mask” that identifies the desired area for observation (e.g. a state border). Cropland area in each state was isolated by combining a state border mask with a cropland mask developed by the African Soil Information Service (AfSIS 2015). This cropland mask separates out urban and heavily wooded areas so that the pixels associated with these areas are not included in the spatial

⁹ NBS production data were published in two survey reports, NBS (2007) and NBS (2011a). Production data reports from NBS, the Kano State Agricultural and Rural Development Authority (KNARDA 2014), which is the official title of the ADP in Kano State, and the Niger State ADP (n.d.) were obtained during fieldwork in 2014. All are available from the authors on request.

¹⁰ The ADP in Kano State is named Kano State Agricultural and Rural Development Authority (KNARDA).

¹¹ See Appendix 2A in Hatzenbuehler (2016) for a more thorough discussion of how these data were obtained.

averages.¹² Monthly NDVI measures for each state were gathered for the period January 2001 to December 2009, because price data were unavailable prior to 2001 and the production data were only available up to 2009. The prices, all obtained from NBS (2011b), are aggregated from urban areas in each state.¹³

6. Empirical results

The results presented here are summarised from a comprehensive set of results to simplify reporting and presentation. Comprehensive results are available from the authors upon request.

6.1 Correlations of production estimates across sources

State-level cross-source correlations for production estimates are presented in Table 1. A positive correlation coefficient implies close co-ordination between sources. The results show that, for Kano and Niger states, the NPAFS estimates are relatively more highly correlated with the ADP data than are those of NBS across all crops (cowpeas estimates were the primary exception). Since NBS had relied solely on ADP data prior to the implementation of the 2004/2006 survey, the apparent poor correlation between NBS and ADP estimates implies that this survey and the subsequent estimates diverged from ADP estimates. Since NPAFS estimates are closely aligned with the ADP estimates for all crops except cowpeas, the same divergence applies for the NPAFS and NBS estimates. There is variation across states and crops in the degree to which NBS and NPAFS estimates are correlated. They are highly correlated for sorghum and cowpeas for Borno and Kano states, but poorly correlated for millet for those states. There is poor correlation for all crops between NBS and NPAFS estimates for Niger State. Since there are only three out of 15 combinations of NBS and NPAFS correlations that are statistically significantly different from zero at the 1% significance level (maize and sorghum for Borno State and rice for Kano State), the choice to use data from one source over another will likely lead to different inferences with regard to intertemporal variation.

¹² A description of the methods used for the construction of the cropland mask can be found in the following AfSIS blog post: <http://africasoils.net/2015/06/07/new-cropland-and-rural-settlement-maps-of-africa/>. In addition, the R code used to create an analogous cropland mask for Tanzania, which contains further details of the methods, was published by Dr Markus Walsh, Senior Research Scientist at AfSIS and can be found on the following website: https://github.com/mgwalsh/Geosurvey/blob/master/TZ_GS_ensemble.R

¹³ There are a few issues with these price data. The millet data for all states for 2008 were obviously subject to a transcription error, so they were excluded. Also, Borno State data are not available for 2001, and the same applies for Kano State for 2008.

Table 1: Correlation coefficients for crop production estimates across state-level sources for Borno, Kano and Niger states, 2001 to 2009

	ADP:NBS	ADP:NPAFS	NBS:NPAFS
Borno State			
Cowpeas	0.69**
Maize	0.96***
Millet	-0.64
Rice	0.34
Sorghum	0.82***
Kano State			
Cowpeas	0.01	-0.08	0.71**
Maize	-0.91	0.99***	-0.87
Millet	0.43	0.72**	0.46
Rice	0.79**	0.89***	0.92***
Sorghum	0.52	0.97***	0.67**
Niger State			
Cowpeas	-0.09	0.50	0.26
Maize	0.37	0.99***	0.35
Millet	-0.34	0.99***	-0.36
Rice	0.37	0.81***	0.32
Sorghum	-0.01	0.60*	-0.36

Note: A positive correlation coefficient suggests close cross-source co-ordination. A correlation coefficient that is statistically significantly different from zero is indicated by ***, ** or *, which represents the associated 1%, 5% or 10% significance level. Kano State ADP estimates for 2001 are missing, so the estimates including the Kano ADP estimates are for the period 2002 to 2009.

6.2 Correlations of production estimates and NDVI

The results of the state production estimate and NDVI correlation analysis are shown below in Table 2. In order to simplify the reporting of results, the reported correlation coefficient for each crop is that which is the highest out of the possible source and NDVI time interval combinations.

The results in Table 2 show that the estimates of the correlation between production and NDVI are generally low, but there is variation across states. The average estimated correlation coefficients are higher for Kano State than those for Borno and Niger states. The correlation coefficients for Kano State cowpeas and millet estimates are statistically significantly different from zero at the 5% significance level. This implies that Kano State estimates for these crops appear to have followed changes in vegetation growth over time. There is variation across states with regard to which source was associated with the highest estimated correlation coefficient. For Borno and Niger states, estimates from either NPAFS or ADPs were more highly correlated with NDVI than were those from NBS. The opposite was found for Kano State. The broadly low estimates across states and crops (cowpeas, maize and millet in Kano State are the primary exceptions) implies that the production estimates do not in general reflect intertemporal changes in vegetation.

Table 2: Summarised correlation analysis of production with NDVI for Borno, Kano and Niger states for the period 2001 to 2009

	Borno State			Kano State			Niger State		
	Source	NDVI time interval	Corr.	Source	NDVI time interval	Corr.	Source	NDVI time interval	Corr.
Cowpeas	NPAFS	GS	0.12	NPAFS	GS	0.75**	NPAFS	Peak	0.44
Maize	NPAFS	GS	0.07	NBS	GS	0.62*	ADP	Peak	-0.10
Millet	NPAFS	Peak	-0.24	NBS	Peak	0.67**	NBS	GS	0.49
Rice	NBS	Peak	0.07	NBS	Peak	0.08	NBS	GS	0.21
Sorghum	NPAFS	GS	0.05	NPAFS	Peak	0.14	NBS	Peak	0.23

Note: The possible sources are described in the data section, and the NDVI measures with abbreviations are in footnote 9. A positive estimated correlation coefficient is expected, and the estimates with the expected sign are in bold. A correlation coefficient that is statistically significantly different from zero is indicated by ***, ** or *, which represents the associated 1%, 5% or 10% significance level.

6.3 Correlations of production estimates and prices

Table 3 shows the degree of correlation between production estimates and harvest month prices. In order to summarise the results, the estimated correlation coefficients that are reported are those that were closest to -1 out of all source and harvest month price combinations.

Table 3: Summarised correlation analysis of production with harvest month prices for Borno, Kano and Niger states for the period 2001 to 2009

	Borno State			Kano State			Niger State		
	Source	Price mo.	Corr.	Source	Price mo.	Corr.	Source	Price mo.	Corr.
Cowpeas	NBS	Oct.	0.04	NBS	Sept.	-0.53	NPAFS	Nov.	-0.50
Maize	NBS	Nov.	0.33	NBS	Nov.	-0.56	NBS	Nov.	0.33
Millet	NPAFS	Nov.	-0.51	NBS	Sept.	0.18	NBS	Nov.	-0.56
Rice	NPAFS	Sept.	0.52	NPAFS	Oct.	0.76	NBS	Nov.	0.56
Sorghum	NBS	Nov.	0.38	NPAFS	Oct.	0.28	NBS	Nov.	-0.53

Note: The possible sources are described in the data section, and the price months are described in the subsection on agricultural production/NDVI and prices. A negative estimated correlation coefficient is expected, and the estimates with the expected sign are in bold. A correlation coefficient that is statistically significantly different from zero is indicated by ***, ** or *, which represents the associated 1%, 5% or 10% significance level.

The results in Table 3 diverge from expectations, since only six out of 15 estimates had the expected negative sign. Of those, all had low absolute values and none were statistically significantly different from zero at the 10% significance level. Millet in Borno State was the only crop with an inverse relationship between production and prices, but there were three crops with this relationship for Niger State. Cowpeas was the only crop for which there were two states (Kano and Niger states) that had a negative correlation coefficient. These results imply that either the production estimates or prices do not reflect growing conditions in these states.

6.4 Correlations of NDVI and prices

The results in Tables 2 and 3 show that production estimates were not highly correlated with either NDVI or prices, although there were some exceptions for the NDVI correlations (mainly for Kano State). This implies that the production estimates may not reflect real conditions broadly, but this depends on the degree to which NDVI and/or prices are realistic proxies. To test whether the NDVI and prices capture similar fluctuations in market conditions as expected, the correlation between them was estimated. The results are presented in Table 4, with only the correlation estimates closest to -1 reported.

Table 4: Summarised correlation analysis of NDVI with urban prices for Borno, Kano and Niger states for the period 2001 to 2009

	Borno State			Kano State			Niger State		
	Price mo.	NDVI measure	Corr.	Price mo.	NDVI measure	Corr.	Price mo.	NDVI measure	Corr.
Cowpeas	Nov.	GS	-0.34	Sept.	GS	-0.70**	Oct.	GS	-0.51
Maize	Oct.	GS	-0.51	Sept.	GS	-0.67*	Sept.	GS	-0.25
Millet	Nov.	Peak	-0.38	Nov.	GS	-0.40	Oct.	GS	-0.26
Rice	Nov.	GS	-0.09	Nov.	GS	-0.44	Sept.	Peak	-0.27
Sorghum	Nov.	GS	-0.25	Nov.	GS	-0.59	Oct.	GS	-0.54

Note: The NDVI measures with abbreviations are in footnote 9, and the price months are described in the subsection on agricultural production/NDVI and prices. A negative estimated correlation coefficient is expected, and the estimates with the expected sign are in bold. A correlation coefficient that is statistically significantly different from zero is indicated by ***, ** or *, which represents the associated 1%, 5% or 10% significance level.

The results are now more consistent with expectations, as all of the estimates have the expected negative sign. However, only three were statistically significantly different from zero at the 10% significance level, of which two were from Niger State, showing greater price response there. Kano State is home to a commercial hub, and urban prices in Borno State are highly linked to those in Kano State (Hatzenbuehler *et al.* 2017). So urban prices in Kano and Borno states are determined less by local production than prices in other markets (and, inter alia, by growing conditions in those markets), while the opposite is the case for Niger State.¹⁴ Even stronger results would be expected if the prices were not aggregated at the state level, but rather were local prices and especially from rural markets, since then the prices used in the empirical analysis would be more closely aligned with the spatial market theory. Longer time series would be helpful as well.

These results have implications for the use of remote sensing information to verify and/or form agricultural production estimates. These include: 1) if prices are chosen as objective, on-the-ground information with which to compare production estimates and NDVI measures, then economic theory and logic are needed to form expectations on the strength of the relationships between these variables; and 2) the use of local rather than aggregated prices, which would lead to less noisy results.

¹⁴ The estimation of the correlation between the NDVI and urban prices using a larger NDVI scope that represents growing conditions in the cropland area of Northern Nigeria, rather than in the smaller state border areas, yields, in most cases, even stronger results. This estimation was done with the same methods as were used to obtain the results in Table 4. The results, with statistical significance designation and levels as defined below Table 4, are: 1) Borno: cowpeas, -0.62*; maize, -0.68*; millet, -0.58; rice, -0.52; and sorghum, -0.63*; 2) Kano: cowpeas, -0.46; maize, -0.70*; millet, -0.36; rice, -0.37; and sorghum, -0.57; and 3) Niger: cowpeas, -0.59*; maize, -0.33; millet, -0.36; rice, -0.48; and sorghum: -0.61*.

6.5 Assessment of national estimates

The broadly poor degree to which production estimates in the analysed states reflect growing conditions implies that it is unlikely that national production estimates will reflect growing condition changes. Table 5 shows the estimates for the correlation between national production estimates and the annual average growing season NDVI averaged across the national cropland. The national production estimates were obtained from the datasets published by the same international sources, namely AMIS-FAO, USDA-PSD and FAOSTAT, and the main national sources, namely NBS and NPAFS, which were discussed in the overview section. Out of 21 crop and source combination estimates, only five had the expected positive sign and none were statistically significantly different from zero at any level of significance. These results imply that both national and international source estimates for national production do not reflect intertemporal changes well under growing conditions.

Table 5: Correlation coefficients for estimates of Nigerian national crop production and average growing season NDVI for Nigerian cropland for 2001 to 2009

	AMIS-FAO	USDA-PSD	FAOSTAT	NBS	NPAFS
Rice	-0.18	-0.28	-0.15	-0.42	-0.40
Maize	-0.35	-0.20	-0.26	-0.40	-0.33
Millet	...	0.55	0.05	-0.16	-0.39
Sorghum	...	0.29	0.31	-0.15	-0.43
Cowpeas	0.18	-0.50	-0.19

Note: A positive estimated correlation coefficient is expected, and the estimates with the expected sign are in bold. A correlation coefficient that is statistically significantly different from zero is indicated by ***, ** or *, which represents the associated 1%, 5% or 10% significance level.

7. Concluding remarks

This study provides a new way to evaluate the quality of existing production data using two objective types of information on market/growing conditions (NDVI and prices) that are readily available, even in relatively information-poor developing countries such as Nigeria. NDVI data are freely available online (GSARS 2015) and crop prices are commonly gathered. Thus, the method is replicable for the evaluation of other agricultural production data in other countries and regions.

The qualitative assessment and quantitative results imply that the use of time series of Nigerian state- or national-level agricultural production estimates in empirical market analyses is broadly problematic. However, quality is not the only aspect of concern with these data. Timeliness is also a concern. The most recent available production estimates from national sources are from 2012 (which are plausibly forecasts from 2011 estimates). Delays in data reporting do not provide a conducive environment for the provision of high-quality data. A comment period that follows the release of an initial estimate can yield additional information from engaged stakeholders, which could be used to encompass more information into estimate formation. However, allowing time for comments would only be useful if all were received before market participant attention shifts at the start of the next crop year.

While this study has provided insights into the current state of agricultural production data in Nigeria, any strategy to improve these data must take into consideration the poor current funding environment for agricultural extension activities in general (NAERLS and FDAE 2013; AMIS-FAO 2014). Strategies to improve upon the status quo would ideally encompass a mix of traditional and new, cost-saving technologies in order to improve data quality at the lowest cost. NDVI information could be used to form smaller, but more representative, samples, which would minimise on-the-ground survey implementation costs while maintaining quality standards (GSARS 2015).

Political will is needed to support both the further in-depth study of this issue and the implementation of sustained strategies for the improvement of the quality and timeliness of agricultural production estimates. Until these necessary investments are made, however, agricultural policymakers, traders and farmers will continue to make decisions in the dark.

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