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Short-term acreage forecasting and supply elasticities for staple food commodities in major producer countries

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Abstract

Forecasting food production is important to identify possible shortages in supply and, thus, food security risks. Such forecasts may improve input allocation decisions that affect agribusiness and the input supply industry. This paper explains methods and data used to forecast acreage of four crops that are particularly important staple commodities in the world, namely wheat, corn, rice, and soybeans for major global producer countries. It focuses on forecasting acreage—one of the two major determinants of grain production—3 months before planting starts with publicly available data. To this end, we use data from the period 1991 to 2013 and perform an out-of-sample forecast for the year 2014. A particular characteristic of this study is that the respective acreage determinants for *each country and each crop* are identified and used for forecasting separately. This allows accounting for the heterogeneity in the countries' agricultural, political, and economic systems through a country-specific model specification. The performance of the resulting forecasting tool is validated with ex-post prediction of acreage against historical data.

Keywords: Acreage forecasting, Supply response, International prices, Staple crops, Price expectations

JEL: Q11, Q18, Q13

Background

Food insecurity remains to be a critical challenge to the world's poor today. According to recent estimates by the Food and Agriculture organization (FAO), one in nine people in the world and about a quarter of those in Sub-Saharan Africa are unable to meet their dietary energy requirements in 2014–2015 (FAO 2015). The focus of this study is not food insecurity and hunger per se. It instead addresses one major component of food security, that is, food production. Although a range of factors influence global food security (FAO 1996), food production plays a major role (Parry et al. 2009). In this paper, we seek to analyze the extent to which production of staple crops in major producer countries can respond to changes in output and input prices. Our focus is on production of the world's principal staple crops, namely wheat, rice, maize, and corn. These crops are crucial for the fight against global food insecurity since they are major sources of food in several parts of the world, comprising three quarters of the food calories in global food production. Maize, wheat, and rice, respectively, are

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the three largest cereal crops cultivated around the world. According to data from FAO (2012), they make up more than 75 and 85 % of global cereal area and production in 2010, respectively. Our analysis focuses on data from 11 major crop producer countries for the 1991–2013 period. Our study countries account for greater than 90 % of global production for soybeans, above 60 % for each of wheat and maize, and nearly half of the global rice production during this period.

Given this backdrop, we develop a short-term acreage response model for the aforementioned key staple crops for major producing countries. In general, agricultural producers respond to own and competing output prices, input prices, price volatility, and other variables (Chavas and Holt 1990; Coyle 1993). Some variables such as rainfall and unexpected policy changes may not be available before planting. Thus, our estimations include the most important variables that are observable about 3 months before the planting season starts. Producers respond to prices and other factors in terms of their land allocation for different crops at planting time (Just and Pope 2001). Since harvest prices are not realized at the time of planting, producers rely on their price expectations for their production decisions. Depending on the crop calendars of each country, we use planting time cash prices and futures prices in order to proxy producers' expectations in the respective acreage response models. These prices contain more recent price information for producers, and they are also closer to the previous harvest period, conveying possibly new information about the future supply situation. Besides own and competing crop prices, we include fertilizer prices, oil prices, and other variables that are relevant for the specific country.

Because global agricultural markets exhibit high frequency volatility, an annual model would do little to capture intra-annual price dynamics and shocks. Thus, we develop an econometric model that enables us to forecast the cultivated area of each crop using intra-annual data. To this end, we develop country- and crop-specific acreage response models. This allows us to account for the large heterogeneity in the countries' agricultural, political, and economic systems in a country-specific model specification. While a panel data fixed effects model also enables to capture time invariant heterogeneity across countries, it only yields average effect sizes of the variables of interests on acreage.

Forecasting acreage before the start of planting is crucial for several reasons. First, it serves as an indication of how much food will be available in the subsequent harvest season in the respective countries and for the respective crops. The selected countries in our acreage forecasting models are major players in the global food market, as are the four crops key staple crops in many countries. In other words, forecasting the amount of area allocated to these crops in these countries can be a sound signal to availability of food (a shortfall or an excess) in the international market. This has significant implications for global food security situations, in particular in food deficit (food importing) countries. For a given yield per hectare of land, forecasting acreage is an important first step in understanding and forecasting the entire production of the major crops. Second, the crop acreage elasticities indicate the extent to which food production (through acreage adjustments) responds to scarcity. Having country-specific estimates, the findings inform which countries can respond to prices more strongly. Third, it provides key information for input and crop protection supply industries to adapt their productions accordingly.

Our short-term models are validated using historical data. As will be discussed later, in nearly all cases our estimations have the expected directional changes, and the estimated confidence intervals provide an additional risk assessment of the likely range of area allocation.

Methods

Acreage response model

A basic econometric supply model explaining acreage of a certain crop is formulated as a function of its own and competing crops' harvest-time prices, input prices, and other exogenous factors. The producer makes his or her crop acreage choices subject to output prices that are not known at the time of planting. Thus, expected rather than realized output prices are used for decision making. Information and expectations change rapidly in the course of a year and models that proxy expectations on previous annual average prices may not capture short-term effects. We instead consider intra-annual price information in order to proxy producers' price expectations in our empirical acreage response models. For example, having information about winter wheat harvest in the USA itself and (partial) spring harvest of corn and soybeans in major producers in the South (e.g., Brazil, Argentina), a US farmer adjusts his price expectations for planting soybeans and corn in the spring season—which will be reflected in the US futures prices and spot prices. Therefore, crop prices 2 to 3 months before planting as well as futures prices maturing in the upcoming harvesting season contain such important information for the farmer.

We use the prior-to-planting season futures prices that mature at harvesting time to represent farmers' price expectations. In efficient markets, futures prices are an unbiased estimator of spot prices when the future contract matures (Gardner 1976; Liang et al. 2011). When no futures prices are available (for example, in countries where commodity exchanges are missing), spot prices also convey relevant information about expected future prices due to inter-temporal arbitrage of grain storage. If stocks are nonzero, current spot prices are in equilibrium with future prices and a change of expected future prices therefore leads to a change of spot prices (Fama and French 1987; Hernandez and Torero 2010).

Models of the supply response of a crop can be formulated in terms of an output, area, or yield response. For instance, the desired area of a certain crop in period t, $A^d_{i,t}$ is a function of expected output prices and a number of other exogenous factors (Braulke 1982):

$$A^d_t = \beta_0 + \beta_1 p^e_t + \beta_2 Z_{t-k} + \varepsilon_t \tag{1}$$

where p^e_t is a vector of the expected price of the crop under consideration and of other competing crops; Z_{t-k} is a set of other exogenous variables including fixed and variable input prices, climate variables, and technological change (the subscript k refers to the length of the lag, which is typically 0 or 1 in our case); ε_t accounts for unobserved random factors affecting crop production with zero expected mean; and β_i are the parameters to be estimated.

Data and country coverage

Data sources

In general, we use planted acreage (from national agricultural statistical offices) of each crop as a dependent variable in our econometric estimations.[1] However, for countries where we do not obtain data on planted acreage, we instead use data on harvested acreage from the FAO of the United Nations, from the United States Department of Agriculture (USDA) or from governmental sources as a proxy. Table 1 shows the correlation coefficients between harvested and planted area for those countries where we have obtained planted acreage data from national statistical offices. The correlation coefficients are mostly (except in the case of wheat for the USA) close to unity, indicating that data on harvested acreage can be used as good proxy for planted acreage in our econometric models.

The explanatory variables, as indicated in the equation above, include spot, wholesale and/or futures output prices, crude oil and fertilizer prices and indices, and minimum support output prices in the case of India. We typically take input and output price information that is available 3 months before planting starts. However, whenever we do not have such information—3 months before planting—we take the recent available value, which is 4 or 5 months before planting. We obtain all crop futures prices from the Bloomberg database, except for China where they are extracted with the TDX stock software. International monthly and annual crop spot prices, crude oil, and fertilizer prices were obtained from the World Bank commodity price database.

Crop calendar information is obtained from two sources: the General Information and Early Warning System (GIEWS) of the FAO and the Agricultural Market Information Systems (AMIS). The Appendix reports part of the crop calendar information that is not available in the aforementioned related publication of Haile et al. (2014).

Study countries

We include the major producing countries of the selected crops in our acreage forecasting models. For instance, our study countries contribute about 90 and 65 % of the global area under soybean and wheat cultivation respectively (Fig. 1).

While the USA has been the dominant producer of soybeans for a long time, large soybean expansions are observed in Brazil and Argentina during the recent decades. According to data from the Foreign Agricultural Service (FAS) of the USDA, the latter two countries alone accounted for half of the total soybean production in the 2013/2014 marketing year. The other countries for which we estimate a soybean acreage model is Ukraine because it is a country with one of the fastest soybean acreage expansions in the last few years. Each of the USA, India, the Russian Federation, and China cultivates slightly above a tenth of the global wheat area (during the 2001–2010 period). China and India alone contribute close to half of the global land under rice cultivation.

Figure 2 depicts the variability of global and country level area harvested since 2000. Figure 2 illustrates that variability of acreage is smaller in countries with relatively

Table 1 Correlation coefficients of planted and harvested area data

Country/crop	Correlation coefficient		
	Wheat	Soybean	Corn
Argentina	0.992	0.963	0.983
Australia	0.878		
Brazil		0.955	0.996
Canada	0.890		
USA	0.759	0.990	0.991

Correlation coefficients were calculated using harvested area data obtained from FAO-AMIS and planted area from national statistical sources

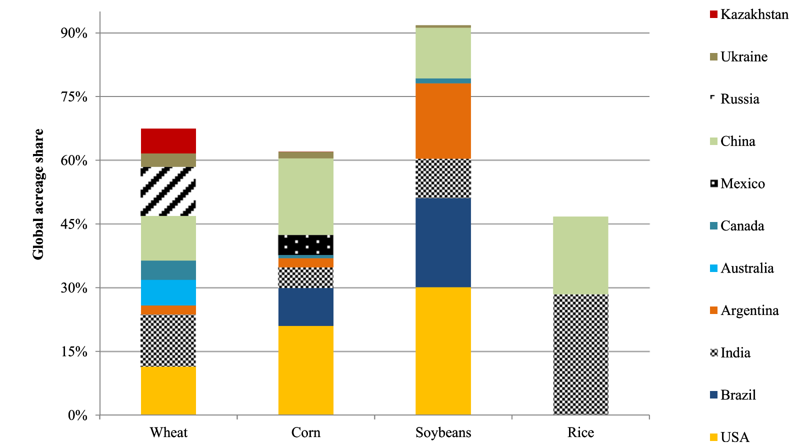

Fig. 1 Acreage share of countries included in our forecasting tool

larger area under cultivation of each crop. More specifically, we observe low area volatility in big producers such as Brazil, China, India, USA, and the world aggregate, whereas we observe large volatility of corn and wheat in Argentina, wheat in Canada, corn in Mexico, and all crops in the Ukraine. The volatility of rice and wheat acreage is lower than the volatility of soybean and corn acreage at a global level, whereas it depends on the size of the area within each country. National policies, however, also play an important role for affecting acreage volatility: Prices and input costs in countries with high government subsidies like India are much more stable than in market-oriented economies like the USA. However, larger price volatility may mean more volatile acreage allocation.

As shown in a related research paper by Haile et al. (2015), global short-term yield response to prices and price risk is of similar magnitude to global acreage response. In other words, higher crop prices are an incentive not only to expand crop acreage but also to intensify production and to invest into higher yields through larger applications of modern inputs, crop protection, and other land management efforts. Forecasting acreage is therefore an important first step in understanding and predicting the entire production of the major crops. In this section, we provide brief background information on our study countries.

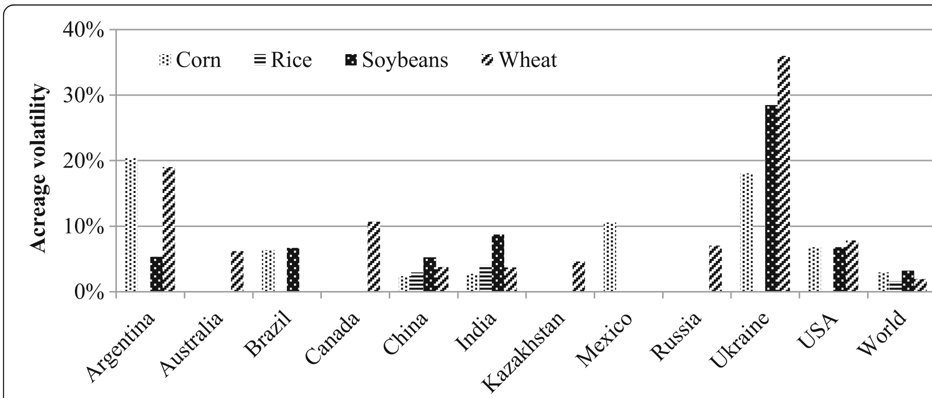

Fig. 2 Volatility (standard deviation of the log returns) of different crops in different countries (data from 2000 to 2014). Notes: We find the rule of thumb that the bigger the area of a specific crop in a specific country, the lower the volatility

Argentina is one of the major exporters of soybeans, typically after it is processed within the country. As a result, soybean area has steadily increased over the past 25 years. Consequently, Argentina comprises of close to 20 % of the global land under soybean cultivation as of the decade 2000–2010 (on average). There are two soybean seasons in Argentina: harvest of the major soybean season starts in April before the minor one starts a month later. For our analyses, we use domestic output prices in pesos per ton instead of international prices since domestic prices exhibited higher increases in level and variability following several exchange rate policy adjustments in the country over the course of the study period. The domestic prices are obtained from the Integrated Agricultural Information System (SIIA) of Argentina. However, international prices are considered for wheat acreage as the model fit improves.

Australia is one of the world's key exporters of wheat although it only comprises slightly above 5 % of the global wheat area cultivation. Some studies indicate that the Australian wheat harvest failure contributed to the 2007–2008 price spikes (Trostle 2008; von Braun and Tadesse, 2012). The Australian global share of land acreage allocated for soybeans and corn is relatively small, and that of rice is negligible. Consequently, we estimate a model for Australian wheat acreage only. We obtain planted wheat acreage data from the Australian Government Department of Agriculture and Australian wheat prices from the Economic Research Service (ERS) of the USDA.

Brazil is a key producer of soybeans and corn accounting for about a quarter and a tenth of the global soybean and corn cultivation, respectively. Harvesting of the first out of the two corn seasons takes place in late February and March, while the second harvest is between May and July (see Appendix). Production of the first corn is largely used for the domestic feed market, whereas the second corn is primarily exported (USDA 2013b). Traditionally, first-crop corn had been the larger of the two while the second-crop corn was labelled as *safrina* (little crop). Yet, there seems to be a tendency of moving to the second corn in Brazil in recent years arriving at 55 % second-season corn production in 2012/2013. Since Brazilian farmers are typically large and commercialized, we used futures prices from the Chicago Board of Trade (CBOT) to proxy farmers' price expectations. March corn and soybean futures prices are used for the first corn and soybean acreage and September corn futures prices for the second corn season. These futures are traded 3 months before planting starts.

Canada is a key producer of wheat, and it exports wheat mostly to the European Union and to a small extent to the USA. Planting of wheat takes place in the spring season. We obtain planted wheat acreage data from CANSIM—Canadian socioeconomic database of statistics Canada. Fertilizer and crude oil prices are obtained from the World Bank commodity price database, and we use futures prices traded at the CBOT 3 months before planting starts in Canada.

China is the biggest producer of rice and wheat and an important producer of corn and soybeans. Corn, soybeans, and wheat are mainly produced in the North, whereas rice is mainly grown in the South with the Yangtze River as an approximate boundary. There are three different seasons for rice: early crop rice is grown in southern provinces and along the Yangtze River and consists mostly of *indica rice*; intermediate (mid) and single-crop late rice, mostly *japanoica*, is grown in the southwest, the northern areas as well as along the Yangtze River. Double-crop late rice is grown after harvest of the early crop in the southeastern parts and constitutes a second *indica* crop where rice is grown. Therefore, *indica* prices have been used for the estimations of the early and late rice whereas *japanoica* rice prices have been used for the middle rice estimations. Depending on the region, there are different seasons for corn and wheat. As more than 70 % of the corn is grown in the North, the estimation is done using data available 3 month before planting in the North. Winter wheat constitutes about 90 % of the total wheat production in China. International prices as well as national future prices are used for the forecast. As future prices are only available from 1995, 2000, and 2006 for soybeans, wheat, and corn, respectively, international prices, converted into Yuan with the appropriate exchange, were used for the time period before. Data for the crop futures was obtained with the free TDX stock software. Daily data is provided for the futures and the exchange rate, so the monthly averages were calculated from this data. All prices were deflated by the consumer price index (CPI). A continuous CPI with 1990 as base year was constructed from the CPI data which is provided as a change for the last 12 month, i.e., for every month, the index is 100 for the same month in the previous year.

India has the biggest wheat and rice areas in the world. However, due to low yields, it is the second biggest producer after China. Furthermore, India is a big producer of soybeans and corn. Areas for wheat, corn, and rice have slightly increased in recent years while they have increased significantly for soybeans. There are two seasons for rice and corn but only one for wheat and soybeans. For both rice and corn, *kharif* is the main season with around 85 % of the total production volume for each crop while the remainder is harvested in the less important *rabi* season. Yearly minimum support prices (MSP) are set a couple of month before planting by the central government, sometimes with top-ups by federal states. These open-end procurement prices are guaranteed to farmers who sell to the government but higher profits may be obtained by selling to private market actors if the market prices are higher. Apart from setting these MSPs, there are many other government market interventions including large public stock holding and grain subsidy. Data on area planted are neither reliable nor continuously available leading to the use of the harvested area as a proxy. To account for both the possibility to sell to the government for the guaranteed MSP and to sell to private market actors for potentially higher wholesale price, the regressions use the MSPs as well as the difference between the MSP and wholesale prices. All prices were deflated by the CPI. Therefore, season-wise data was obtained from the Commission for Agricultural Costs and Prices. For rice, no good prediction could be obtained without including rainfall. Rainfall during planting time seems to play an important role for cultivation of rice in India. Because rainfall data are not available in advance, the forecasting accuracy of our Indian rice acreage model is poor.

Kazakhstan is an important producer of cereals (mainly wheat) in Central Asia. Wheat acreage in Kazakhstan accounts for about 6.5 % of the global acreage share in 2012. The bulk of the crop is sown in the spring season—in April and in May. The total area planted under wheat represents over 85 % of total cereal production in the country. Given the small share of other grains such as corn and soybeans in the country, we have developed a model for forecasting wheat acreage only. We used international monthly prices 3 months before planting of wheat in Kazakhstan in our wheat acreage response model. Harvested wheat area from the USDA is used as a proxy for planted acreage.

In Mexico, corn is by far the most important agricultural commodity in terms of both production and consumption. Mexico is the sixth largest corn producing country in the world, contributing above 5 % of the global land under corn cultivation. However, it is also a key importer of corn. Corn is produced in all regions of the country and grows throughout the year. While the spring-summer corn is sown between April and September, the fall-winter corn is harvested October through March in the next calendar year. The spring-summer season corn accounts for about three quarters of the total corn production in the country. Because corn is used as both food and feed, Mexico—-despite its high production—stands to be one of the world's largest corn importers, where the USA has been by far the largest supplier (USDA 2013a).

The Russian Federation is a key producer of wheat. It constitutes slightly above 10 % of the global area under wheat cultivation. Wheat production in Russia has been more or less constant over the past two decades, ranging between 20 and 25 million hectares. However, there is a recent increase in production of corn and soybeans, especially since 2006/07. About two thirds of the total wheat production is usually winter wheat, which is planted September through October.

Ukraine has become an important producer of corn and soybeans in recent periods, although wheat covers a larger area. Planting of soybean and corn takes place during the spring season, whereas about 95% of Ukraine wheat is winter wheat. Wheat is planted in autumn. We use the monthly international prices from the World Bank commodity price database to forecast these crop areas in Ukraine.

The USA is a major producer of corn, soybeans, and wheat. It is the world's largest producer and exporter of corn while constituting about a fifth of the global area cultivation. Soybeans rank second among the most-planted field crops in the USA making it the largest producer and exporter of this oil crop. The USA cultivates about a third of the global soybean acreage, produces about 10 % of the world's wheat, and supplies about a quarter of the world's wheat exports. About a third of the total wheat production in the US is planted in the winter season. As a result of their global importance, we estimate acreage response models for all three crops. Planted acreage is obtained from the USDA website and futures prices from the CBOT exchange serve as good proxies for US farmers' price expectations.

Estimation technique

Using a times-series approach, the acreage demand equations can be specified as a linear function of the following form:

$$A_{t,i} = \beta_{0,i} + \sum\nolimits_{j}^{n} \alpha_{ij} E_t\left(p_{ij}\right) + \beta_1 Z_{t-1,i} + \gamma t + \varepsilon_{t,i} \tag{2}$$

where $A_{t,i}$ denotes the acreage planted to the ith crop ($i \in$ {wheat, corn, soybeans, rice}). The time trend captures smooth trends in such as technological changes or output demand changes resulting from increased biofuel mandates, income, or population. All the other variables are as defined above.

Our general procedure is to have different model specifications for each country and each crop which differ based on the crop calendar and other characteristics of the country, including planting and harvesting time, existence of futures exchange, and relevance of competing crops. This gives us a set of a priori specifications based on theoretical considerations. We then run regression models on the respective model specifications with different crop prices (e.g. domestic wholesale spot prices, futures prices, international spot prices) and input prices (fertilizer and oil prices). After testing several model specifications, we ultimately choose the model with the highest predictive power adjusted for the number of explanatory variables (adjusted R^2) and with the smallest root mean squared error (RMSE). The final model is the one that best explains acreage with the minimum input data requirement. Models that use data not easily available a few months before planting (e.g., rainfall) were considered only if the predictive power remained too low otherwise. We have taken special care in comparing estimates from alternative model specifications by retaining the same dependent variable. In order to minimize the risk of a pre-test bias, we additionally considered the Bayesian information criterion (BIC) for our model selection.

While higher own crop prices imply larger expected profits for acreage expansion (positive coefficient), higher prices of competing crops induce producers to shift land away from the respective crop (negative coefficient). Fertilizer and oil prices indicate production costs, and the higher such costs, the lower the incentive to cultivate more land. Thus, we expect a negative coefficient for these variables. However, higher oil price also indicate more demand for biofuel and may have a positive coefficient, especially for corn. High fertilizer prices may also have a positive effect on the acreage of some crops. This is typically the case for soybeans. Soybean production requires little or no nitrogenous fertilizer and higher fertilizer prices therefore may imply that it is less costly to allocate more land for soybean production, shifting away from crops with large fertilizer demand. With the coefficients of these variables for each country and each crop, it would then be possible to forecast acreage.

All variables in the acreage response model in Eq. (2) are transformed to their logarithmic formats in the respective econometric models. Hence, the estimated coefficients can be interpreted as acreage elasticities. Therefore, to calculate the total area, one cannot just take the exponential of the estimated logged variable. Instead, given equation (2) above, one has to calculate $\hat{A} = \hat{\alpha}_0 \exp\left(\widehat{\log A}\right)$ where the "hat" implies that the variables are estimated and $\hat{\alpha}_0 = \frac{1}{n}\sum_{i=1}^{n}\exp(\hat{\varepsilon}_i)$ where n is the total number of observations (Wooldridge 2009).

Before conducting our estimation, however, we need to check for the stationarity of our time series variables. We use the Augmented Dickey-Fuller (ADF) unit root test for this purpose. The results from the ADF test, available upon request, show that nearly all our time series variables exhibit non-stationarity at the 5 % level of statistical significance. Few exceptions with stationary variables include corn and soybean prices in the Indian Kharif corn acreage model; corn acreage in Mexico; wheat acreage in Ukraine; and soybean acreage in Argentina.

Similarly, we test for unit root of all of the time series variables after first differencing. The unit root test results indicate that nearly all the variables in the acreage response models are stationary after first differencing at the 10 % level or less (Table 2). Thus, we instead use the first order difference variables, which are I(0) series, for the empirical model estimations to avoid spurious regression results. The constant is therefore interpreted as a linear trend in the empirical estimations. Furthermore, because autocorrelation is typically a problem in time series models, the Newey-West autocorrelation adjusted standard errors are employed in the econometric estimations.[2]

Table 2 Unit root (ADF) test of time series variables after first differencing (H_o: unit root)

Corn							
Variable	Corn acreage	Wheat price	Corn price	Soy price	Fertilizer price	Oil price	
Argentina	−4.782		−3.689	−3.699	−5.896	−4.408	
China	−3.888		−3.167	−3.629			
Brazil, 1st Corn	−4.822		−5.888	−6.024	−6.178	−4.474	
Brazil, 2nd Corn	−6.524		−4.800		−6.147	−4.474	
India, Kharif	−4.124		−4.282	−5.012			
India, Rabi	−2.993		−3.461				
Mexico	−8.265		−3.247		−4.284	−5.896	
Ukraine	−5.363			−3.138	−4.604	−4.707	
USA	−6.458		−5.356	−5.279	−6.151	−4.474	
Wheat							
Variable	Wheat acreage	Wheat price	Corn price	Soy price	Fertilizer price	Oil price	Wheat diff. WS-MSP
Argentina	−7.111	−4.243		−4.515	−5.896	−4.408	
Australia	−5.671	−5.299			−4.826	−4.804	
Canada	−6.221	−4.044			−4.826	−4.804	
China, winter w.	−2.556	−3.375					
China, spring w.	−1.614	−3.268					
China, all wheat	−2.078	−3.375					
India	−4.653	−6.049					−5.892
Kazakhstan	−2.856	−4.728	−3.766		−4.526	−4.707	
Russian Federation	−4.990	−4.348	−3.215		−4.526	−4.707	
Ukraine	−6.069	−4.088	−4.189	−4.713	−4.604	−4.707	
USA	−6.795	−5.072			−6.151	−4.474	
Soybeans							
Variable	Soy acreage	Wheat price	Corn price	Soy price	Fertilizer price	Oil price	
Argentina	−3.384		−3.495	−3.525	−5.896	−4.408	
China	−4.808		−3.167	−3.629			
Brazil	−6.075		−6.738	−6.517	−6.151	−4.474	
India	−3.476		−2.406	−5.172			
Ukraine	−2.413	−3.952	−3.138	−4.137	−4.604	−4.707	
USA	−3.804		−5.374	−5.543	−6.151	−4.474	
Rice							
Variable	Rice acreage	Rice price	Intern. rice price	Rice diff. WS-MSP	Rainfall		
China, early r.	−2.646	−2.777					
China, middle r.	−2.542	−2.804					
China, late rice	−2.338	−2.020					
China, all rice	−2.519	−2.372	−2.543				
India, all rice	−4.142	−5. 317		−4.239	−5.610		
India, Kharif	−4.030	−4.299		−3.242	−4.448		
India, Rabi	−2.370	−3.983		−3.224	−4.448		

Critical values are −3.750, −3.000, and −2.630 at the 1, 5, and 10 % significance levels (Fuller 1976 p. 373). The results are ADF tests with one lag and a constant for the variables. The Indian rice and wheat prices refer to the MSP

Limitations with regard to our acreage forecast

It is important to be aware of some limitations of our modeling approach, especially with regard to using the estimates for forecasting purposes. One challenge of supply estimates is the limited amount of observations for aggregated national data. Since the empirical models are based on *prices* as the most important (and easily measureable) determinants of supply response, they will have limited predictive power in cases where non-price factors are more important. This may be the case if i) governments implement ad hoc policies and controls; (ii) farmers produce crops mainly for their own consumption; (iii) farmers have limited market access; (iv) farmers selling prices are systematically different from the reference prices we consider (e.g., in case of imperfect price transmission or non-convergence of futures and spot prices); or (v) other subsidies and taxes dilute the incentive role of prices.

As explained above, spot prices at planting time are often good proxies for expected futures prices because there is an inter-temporal dynamic relationship between the two price series. This relationship, however, can change if interest rates, storage costs or storage policies change or if stocks are depleted. Finally, our model assumes a stable relationship between acreage and the explanatory variables, which might be inappropriate for countries experiencing large transformations. To reduce this problem, we typically considered periods after 1991.

Results and discussion

Regression results

Tables 3, 4, 5, and 6 present the regression results for the acreage response models of corn, wheat, soybeans, and rice, respectively. In general, the regression estimates illustrate that own and competing crop prices have positive and negative coefficients respectively, consistent with economic theory. The joint F-test results, which are reported at the bottom of each table, indicate that the acreage models (except in a few cases) are statistically reliable. The adjusted R^2 values are sometimes small but this is not unexpected in time series models with first differences. In some models, the lagged area is included while it is excluded in others. In general, the lagged area should only be included if it increases the explanatory power of the model. Three criteria are used to decide on this: adjusted R^2, BIC, and the statistical significance of the autoregressive coefficient. Usually, these criteria all suggest the use of the same model; whenever they do not, the model that is supported by two of these criteria is chosen. In the last row of the tables, it is indicated which criteria have justified the specific choice.

Corn acreage responds to its own prices with elasticities that range from negligible in Ukraine to as high as 0.6 for second corn in Brazil (Table 3). A 10 % higher corn price, for instance, leads to an expansion of corn acreage by about 4 % in Argentina and by about 6 % of the second corn in Brazil. Not only is the price response of the second-crop corn (also called *safrinha*) in Brazil stronger, it also has a strong positive time trend as reflected by the statistically significant intercept term. In agreement with this finding, the data show that area under cultivation of *safrinha* corn in Brazil took the lead over the first corn (also called *safra*) during the 2012 planting season. Not surprisingly, the intercept term of the first corn crop is statistically significant and negative, indicating its declining trend. US corn acreage responds to own crop price relatively strongly. All other

Table 3 Estimation results for corn

Variable	Argentina	Brazil		China	India		Mexico	Ukraine	USA
		1st corn	2nd corn		Kharif	Rabi			
Lagged own area		−0.588*** (0.196)				−0.579*** (0.113)	−0.637*** (0.150)	0.655*** (0.153)	−0.276* (0.150)
Own crop price	0.382** (0.164)	0.228* (0.123)	0.574*** (0.138)	0.164*** (0.037)	0.124** (0.043)	0.377*** (0.114)	0.140* (0.077)	−0.088 (0.328)	0.488*** (0.101)
Soybean price	−0.372** (0.166)	−0.333* (0.197)		−0.085** (0.036)	−0.048 (0.034)				−0.274** (0.101)
Fertilizer price		0.206*** (0.065)	−0.250*** (0.083)				−0.086** (0.039)	−0.370* (0.207)	−0.035 (0.027)
Oil price	−0.108 (0.113)							0.882* (0.486)	0.021 (0.019) 0.035
Dummy 1995				0.454*** (0.158)					(0.051)
Dummy 2006				−0.78*** (0.173)					
Constant	0.050* (0.024)	−0.055*** (0.016)	0.085*** (0.021)	0.023** (0.009)	0.013 (0.008)	0.092*** (0.021)	−0.004 (0.015)	0.066 (0.084)	0.000 (0.009)
N	24	22	21	23	16	15	22	20	28
Joint F-test (*p* value)	0.003	0.019	0.002	0.000	0.029	0.000	0.002	0.040	0.000
Adj. R^2	0.166	0.388	0.342	0.130	0.186	0.221	0.484	0.326	0.557
Why this specif.?	A, C	A, C	A, B, C	A, B, C	A, B, C	A, C	A, C	A, B, C	A, C

All variables except dummies are in log differences. Figures in parentheses are Newey-West autocorrelation adjusted standard errors. Criteria for selection of specification (with versus without lagged area): A: adjusted R^2 higher in the chosen specification; B: BIC lower in the chosen specification; C: statistical significance of the coefficient for the autoregressive term

$^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$

Table 4 Estimation results for wheat

Variable	Argentina	Australia	Canada	China			India	Kazakhstan	Russia	Ukraine	USA
				Winter	Spring	Total					
Lagged own area		−0.220 (0.144)		0.380** (0.160)		0.379*** (0.132)			−0.563*** (0.152)	−0.438** (0.179)	
Own crop price	0.141 (0.172)	0.140 (0.093)	0.103** (0.050)	0.039 (0.024)	0.160 (0.107)	0.052** (0.024)	0.123* (0.067) (MSP)	−0.011 (0.064)	0.172** (0.070)	0.355* (0.208)	0.286** (0.121)
Soybean price	0.023 (0.253)							0.052		−0.093 (0.528)	−0.069 (0.089)
Corn price								(0.061)	−0.210** (0.090)	−0.348 (0.361)	−0.052 (0.102)
Fertilizer price	−0.345*** (0.117)	0.210** (0.073)	0.159** (0.045)					−0.003 (0.065)		0.123 (0.191)	0.021 (0.019)
Oil price		−0.263*** (0.085)						0.173** (0.067)	0.262*** (0.071)		
Diff. MSP-WSP							0.022* (0.012)				
Dummy 2000				−0.128 (0.114)	−0.880 (0.517)	−0.285** (0.109)					
Constant	−0.007 (0.027)	0.022 (0.018)	−0.026 (0.014)	−0.005 (0.011)	−0.039 (0.026)	−0.002 (0.006)	0.005 (0.006)	−0.017 (0.018)	−0.023 (0.018)	0.002 (0.050)	−0.017** (0.007)
N	23	23	23	20	20	22	29	20	20	20	28
Joint F-test (*p* value)	0.056	0.032	0.007	0.001	0.001	0.000	0.123	0.311	0.008	0.594	0.018
Adj. R^2	0.214	0.301	0.335	0.034	0.020	0.262	0.050	0.061	0.465	−0.068	0.286
Why this specif.?	B, C	A, B	A, B, C	A, (B), C	A, B, C	A, B, C	A, C	A, C	A, C	A, B, C	A, B, C

All variables except dummies are in log differences. Figures in parentheses are Newey-West autocorrelation adjusted standard errors. Criteria for selection of specification (with versus without lagged area): A: adjusted R^2 higher in the chosen specification; B: BIC lower in the chosen specification; C: statistical significance of the coefficient for the autoregressive term

*$P < 0.10$, ** $P < 0.05$, *** $P < 0.01$

Table 5 Estimation results for soybeans

Variable	Argentina	Brazil	China	India	Ukraine	USA
Lagged own area		0.196* (0.097)			0.493** (0.206)	
Own crop price	0.061 (0.059)	0.340* (0.181)	0.300** (0.124)	0.157* (0.084)	0.609 (0.546)	0.265** (0.120)
Corn price	−0.067 (0.059)	−0.203* (0.124)	−0.476*** (0.150)	−0.046 (0.170)	−0.178 (0.457)	−0.255* (0.145)
Wheat price					−0.993* (0.582)	
Fertilizer price	−0.042 (0.038)	−0.086* (0.046)			−0.231* (0.136)	0.025 (0.023)
Dummy 1995			−1.504** (0.552)			
Dummy 2006			2.244*** (0.704)			
Constant	0.060*** (0.014)	0.040*** (0.013)	−0.007 (0.013)	0.039* (0.019)	0.146* (0.082)	0.005 (0.009)
N	24	23	23	17	19	28
Joint F-test (*p* value)	0.24	0.058	0.000	0.147	0.056	0.016
Adj. R^2	0.121	0.199	0.415	0.068	0.347	0.294
Why this specif.?	A, C	A, B, C	A, B, C	A, B, C	A, B, C	A, C

All variables except dummies are in log differences. Figures in parentheses are Newey-West autocorrelation adjusted standard errors. Criteria for selection of specification (with versus without lagged area): A: adjusted R^2 higher in the chosen specification; B: BIC lower in the chosen specification; C: statistical significance of the coefficient for the autoregressive term

$^*P < 0.10$, $^{**} P < 0.05$, $^{***} P < 0.01$

Table 6 Estimation results for Rice

Variable	China				India		
	Early	Middle	Late	Total	*Kharif*	*Rabi*	Total
Lagged own area		−0.532*** (0.081)	0.593*** (0.127)				
Own domestic crop price	0.302*** (0.068)	0.134* (0.074)	0.302*** (0.030)	0.230*** (0.061)	0.189 (0.126)	0.251 (0.429)	0.156 (0.092)
Rainfall					0.201*** (0.049)	0.481* (0.225)	0.161*** (0.056)
Difference MSP-WSP					0.033*** (0.009)	0.063* (0.033)	0.012* (0.006)
Dummy 2008				−0.073** (0.024)			
Constant	−0.033*** (0.009)	0.017 (0.007)	−0.016** (0.007)	−0.011** (0.005)	−0.003 (0.005)	0.004 (0.035)	0.000 (0.005)
N	13	13	14	15	16	16	23
Joint F-test (*p* value)	0.001	0.000	0.000	0.001	0.001	0.042	0.038
Adj. R^2	0.459	0.474	0.768	0.562	0.563	0.230	0.365
Why this specif.?	A, B, C	A, B, C	A, B, C	A, B, C	A, B, C	A, B, C	A, B, C

All variables except dummies are in log differences. Figures in parentheses are Newey-West autocorrelation adjusted standard errors. Criteria for selection of specification (with versus without lagged area): A: adjusted R^2 higher in the chosen specification; B: BIC lower in the chosen specification; C: statistical significance of the coefficient for the autoregressive term

*$P < 0.10$, ** $P < 0.05$, *** $P < 0.01$

factors remaining constant, a 10 % increase in corn price induces about a 5 % expansion of corn acreage in the USA. Acreages of both *kharif* and *rabi* corn in India fairly respond to own crop prices, with short-term elasticities of 0.12 and 0.38, respectively. Not only is the acreage of Rabi corn in India three times more responsive to own crop prices than *kharif* corn, it also has a significant positive time trend. According to the result, acreage of the Indian *rabi* corn has been growing by an annual rate of about 9 %. A rise in own crop price also leads to a statistically significant corn acreage response in China, with a short-term elasticity of 0.16. Corn competes for land (and other inputs) primarily with soybeans. This is reflected by the statistically significant and negative corn-soybean cross price elasticity of corn acreage in most countries including in Argentina, Brazil, China, and the USA.

While corn acreage negatively responds to fertilizer price index (except *safra* in Brazil), it has statistically insignificant response to international crude oil prices (with an exception of Ukraine). As it is theoretically expected, high (input) fertilizer price reduces producers' profit expectations and they tend to shift land away to crops with little or no fertilizer demand. In contrast, a high crude oil price has two opposite effects. On the one hand, higher oil price implies large production cost and hence its effect is expected to be negative. On the other hand, higher oil price imply larger demand for biofuel, and hence for corn, and hence its acreage effect is positive. The net effect seems to be statistically negligible in our empirical estimations, except in Ukraine where the positive demand effect outweighs.

Although elasticities are smaller than for the corn acreage model, wheat acreage in our study countries exhibits a positive response to own prices (Table 4). Price elasticities of wheat acreage range from about negligible in a few countries to about 0.4 % in Ukraine. More specifically, a 10 % higher wheat price induces an expansion of wheat acreage by about 4 % in Ukraine, 0.3 % in the USA, 0.2 % in the Russian Federation, and by about 1 % in each of India, Canada, and China (total wheat). In addition to the MSP, Indian wheat acreage has a statistically significant positive response to the difference between the MSP and the wholesale price. It is also interesting to see that wheat acreage in most of the countries does not show any significant trend over time except in the USA, where it has an annual declining trend of about 2 %. Furthermore, it is also noteworthy to mention the positive coefficient of the international oil price on the wheat acreages of Kazakhstan and the Russian Federation, which is contrary to our expectations. One explanation could be that larger export revenues as a result of higher international oil prices might have a substantial share in the national incomes of these countries and these might (partly) be invested into agriculture.

The results for soybeans are reported in Table 5. Overall soybean acreage positively responds to own prices and negatively to competing crop prices as expected. High fertilizer prices reduce soybean area in Brazil and Ukraine. High levels of price responsiveness are found in Brazil, Ukraine, the USA, and China, whereas lower levels are found in India and Argentina. Our estimated soybean price elasticity of acreage for Brazil (0.34) lies between the spot (0.26) and futures (0.63) price acreage elasticities estimated by Hausman (2012).[3] For China, two dummies have been included because the time series for the prices changed from international price to domestic future prices. Except for China, the constant is positive indicating that soybean area has an increasing trend in the long run. This positive trend is especially high for Ukraine, illustrating the recent rapid soybean acreage expansion in the country. Such trend may be the result of increases in population, income, consumer preferences, and technology. These factors seem to put pressure on land availability for soybean production in most countries.

Table 6 reports the results for rice acreage response. We model rice acreage response in China and India, where half of the world's rice cultivation takes place. Seasonal rice as well as total acreage responses are investigated in both countries. A small number of observations have often prevented us to include more than one or two explanatory variables. Wholesale prices in China are not consistently available for earlier years and international prices turned out to have no predictive power, which is why they are not reported here. This is not surprising because smallholder farmers in both countries do not usually have access to international markets and trade restrictions often limit international price transmission to domestic market. For the individual season rice in China, forecasts are not possible because last year's area and prices reported in the yearbooks are only available ex post, i.e., a few months after the harvest.

However, for the total area, timely available acreage data were taken from the FAO and prices from the agricultural ministry website. This enables forecasting the total rice acreage. A dummy for the year 2008 is included because earlier domestic prices are available from the yearbooks, whereas the later ones are obtained from the TDX software. Competing crop, oil, and input prices are tested but are found to be statistically insignificant and therefore are not reported. The lagged area changes are included for the middle and late rice area in China.

While no clear time trend of the rice area is visible in India, in China there is mostly a slow decrease indicated by the negative constant term. The own price responsiveness is relatively high in both countries but it is statistically significant only in China. In India, the MSP was used as "own domestic crop price" and it has a higher effect than the difference between the wholesale price and the MSP, but the latter is more significant and therefore more consistent among the indsividual observations. As expected, all price variables have positive signs. However, including rainfall makes results much better India. The results show that rainfall is the most important driver of Indian rice area. This limits the area forecasting possibility of the empirical model since predicting rainfall is difficult if not impossible. Interestingly, including a rainfall variable is sufficient to obtain a good fit.

Validation of forecasting power

In order to examine the forecasting power of our models, we use two types of tests. One is a simple quality check of the fitted values to illustrate the level of the residuals. These are the residuals for years that are part of the sample and that we used in the regression. Figure 3 depicts our estimation results—including also the 50 and 90 % confidence intervals—and compares them with the actually observed values for a selection of crops and countries.

Confidence intervals are based on OLS standard errors. We only show a selection of the fitted graphs here; all figures are available upon request. In general, the estimations performed well in predicting the actual values. However, there are some outliers and these mostly occur when there are big sudden changes. Nevertheless, the predictions have often the same direction of change as that of the observed data. Looking at

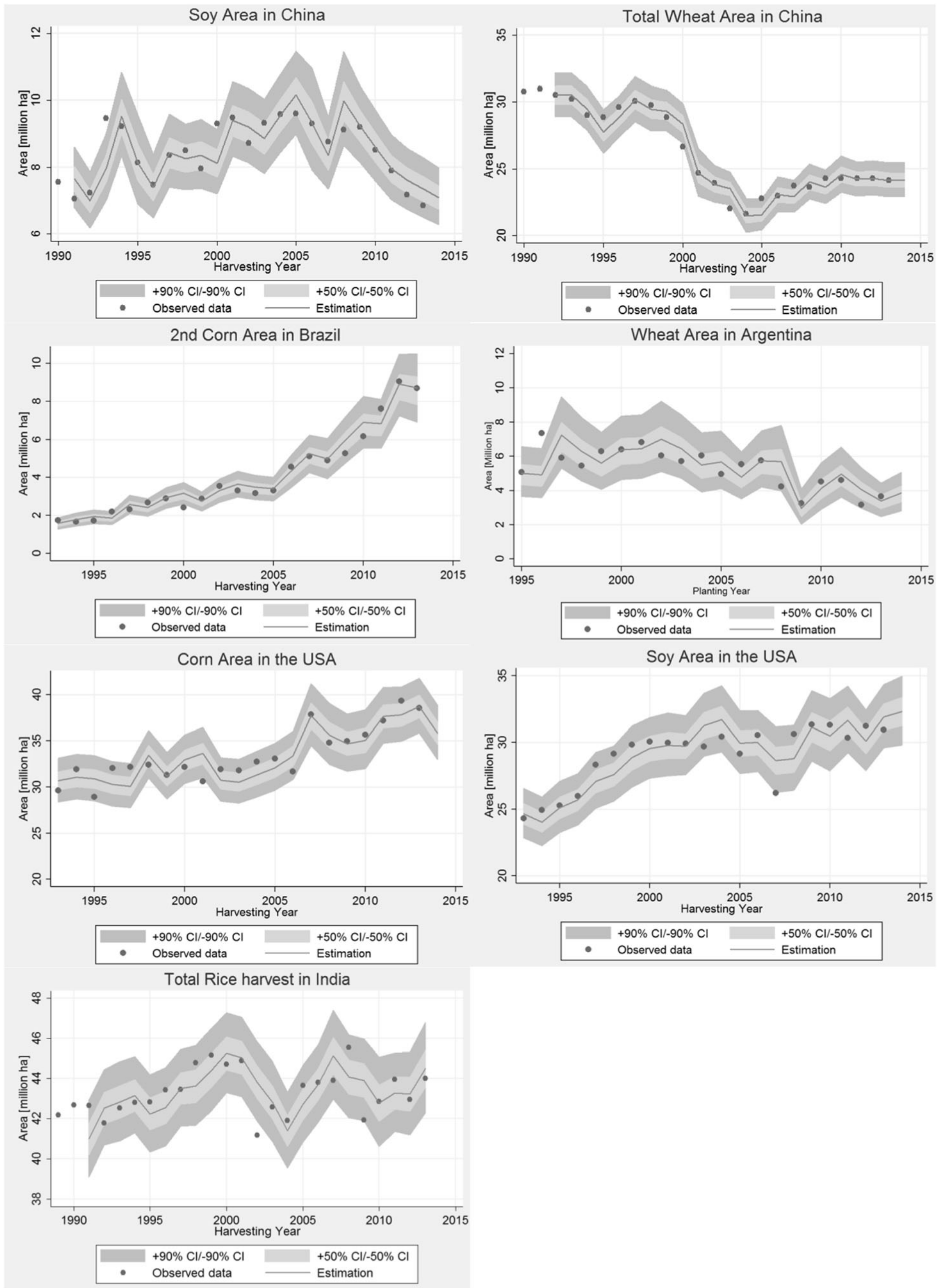

Fig. 3 Comparison of ex-post estimations and confidence intervals with observed area data. Notes: For each crop, two countries are shown as an example except for rice, where only India is shown

soybean area in China, for example, shows that in the year 1993 a big increase in area was forecasted but the actual increase was a lot higher and therefore is even out of the confidence interval. The same holds for the large decline in wheat area in China in the year 2000 where a much smaller decline was predicted. Sometimes but rarely, there are outliers which are not in the confidence intervals an even the direction of change was not predicted correctly as it is the case for the soy are in China in the year 2000. For some countries and crops, the confidence intervals are relatively large while they are smaller for others like wheat in China, corn in the US, or rice in China (consider the scale). Interestingly, the large increase in corn area in the USA in 2007 due to the biofuel mandates are well captured in the graph for corn, whereas the accompanying decrease in soy area in that year is not captured in the graph.

The second way of validation is to compare our latest forecasts with the actually observed values. These latest observations—usually for 2014—are not part of the sample and therefore have not been used in the regressions. Thus, they can be used for out-of-sample validation. Figure 4 illustrates our out-of-sample forecasts showing the point estimates as well as the confidence intervals and compares them with the actually observed data. Only data available 3 months before planting have been used for these forecasts.

A number of interesting observations can be made: (1) all actual areas are within the 90 % confidence interval of our forecasts; (2) almost half of the actual areas are within

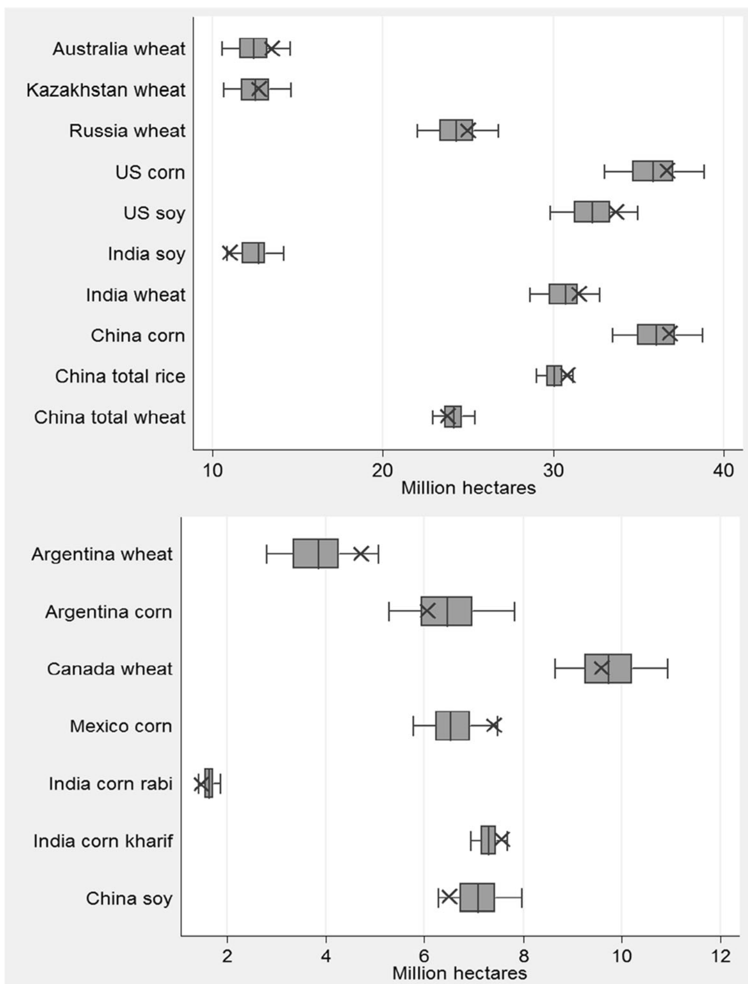

Fig. 4 Comparison of out-of-sample forecasts. Notes: The *boxplots* show the upper and lower 50 and 90 % confidence intervals as well as the point estimate. The observed area is indicated by an *"X" symbol*. For the regressions, data until 2013 are used to forecast area for 2014 for all crops and countries (if relevant data was available). One exception is corn in India, where data until 2012 is used in the regression and the forecast for 2013 is shown above. Areas above 10 million hectares are depicted in the *upper graph* while areas below 10 million hectares are illustrated in the *lower graph*

the 50 % confidence interval, which underlines the validity of our models; (3) while 11 times the actual values were higher than the forecast, they only were lower in 6 cases; (4) the confidence intervals vary in size between the different crops and different countries. Not only do the confidence intervals typically increase when the estimated area increases but also significantly differ for comparable areas, thereby indicating that some forecasts perform significantly better than others. And, (5) forecasts for individual seasons are mostly impossible because the required data are not available in time. The upward-biased forecast related to (3) is primarily driven by countries where we used international rather than domestic prices. This could indicate a shift in the international price transmission dynamics and can be indicative of the need to use domestic price data in order to improve acreage forecasts.

Overall, the forecasts perform well even if many of them only provide a rough estimation due to the wide confidence intervals. The predicted acreage is usually correct in terms of direction. Moreover, the actual data points are mostly in the 90 % confidence interval, showing a high prediction power when validated with historical data. However, the forecasting precision varies significantly from crop to crop and country to country.

Conclusions

A substantial part of the analyses in this paper has been devoted to identify the relevant determinants of acreage supply for each crop and country. This enables us to select the model that provides the best prediction power (high explanatory power) with minimal input data requirement. The price elasticity of acreage estimates are key parameters for forecasting acreage in all the countries. Moreover, the acreage elasticity estimates can serve as a ground proofing and robustness check for other studies that estimate worldwide aggregate acreage elasticities (e.g., Haile et al. 2014). Worldwide aggregate acreage elasticity estimates give an average effect of prices on acreage for each crop, whereas country-specific acreage elasticities can be used as inputs in acreage forecasting applications for the respective countries and crops.

Based on the results reported above, we identify two groups of countries: those with high price responsiveness and those with strong time trends (Table 7). Crop prices are key drivers of acreage in the first group of countries, whereas acreage growth can be expected even when prices do not change or change only slowly

Table 7 Overview of the price sensitive markets and the markets with strong time trends

Crop	Price sensitive markets	Markets with strong time trends
Corn	Argentina (0.38) Brazil (1st 0.23, 2nd 0.57) US (0.49) India Rabi (0.38)	Argentina (0.05) Brazil (1st −0.05, 2nd 0.09) China (0.02) India (Rabi: 0.09)
Wheat	Russia (0.17) Ukraine (0.36) US (0.29)	US (0.02)
Soybeans	Brazil (0.34) China (0.30) Ukraine (0.61) US (0.27)	Argentina (0.06) Brazil (0.04) India (0.04) Ukraine (0.15)
Rice	China early (0.30) China late (0.30) China total (0.23)	China early (−0.03) China late (−0.02)

The respective coefficients are given in parentheses in the latter group of markets. These countries—countries that belong to both groups—have large potential to boost food production and are therefore key in tackling food insecurity and hunger, which are two of the greatest challenges of our time. Countries in the first group respond to food scarcity more strongly, which may suggest existence of sound market institutions. Regardless of market conditions, countries in the second group have large potential (such as abundant land) to produce more. All these countries have a vital role in supplying food to the international market.

Crops with high price responsiveness (i.e., own price elasticity higher than or equal to 0.2) include corn in Argentina, Brazil (both first and second corn), and the USA and *rabi* corn in India; wheat in the Russian Federation, Ukraine, and the USA; and soybeans in Brazil, China, Ukraine and the USA. Furthermore, acreages of early, late, and total rice in China exhibit strong price responsiveness. These findings are interesting from a policy perspective as they indicate institutional differences across countries. While producers in countries with well-functioning financial markets and input and output markets may benefit from higher output prices, this may not be the case in countries where these markets do not exist or function poorly. There are quite a few countries and crops where cropland is expected to grow or decline by more than 2 % per year regardless of changes in prices or costs. Among these countries, soybeans in Ukraine, second corn in Brazil, and rabi corn in India show the highest long-run acreage trends. In these countries, acreage expansion or shrinkage can be expected even if prices remain stable or are slightly changing.

Input costs (fertilizer prices) are important factors for acreage response in most cases. Less obvious is the crop acreage response towards higher oil prices, with mixed (positive and negative) acreage response effects. For instance, increasing oil prices boost acreage expansion in Kazakhstan and the Russian Federation—where revenues from oil exports have a substantial share in respective national incomes and it might be (partly) invested into agriculture.

While we are able to explain historical acreage fluctuations well for most countries and crops, forecasting power is weak for some particular cases. Our model, for instance, has weak explanatory power for wheat acreage in Ukraine and rice acreage in India. Nevertheless, the ARDL acreage models adequately explain historical acreage decisions. The results provide elasticities that can serve as a basis for a timely forecast of upcoming planting season acreage based on the currently and publicly available data in most cases. The calculated point forecast is extended by an interval estimation which helps to assess the likely range of the acreage allocation. This is important to appropriately deal with uncertainties and risks as forecasts are usually uncertain.

It is worth to note that the forecasts are primarily based on price movements as major determinants of acreage. The forecasting tool could therefore be extended by further market analyses based on broader political and economic factors as well as short-term weather events, which are not accounted for by prices but that could potentially influence acreage decisions. Due to small size of observations, this is, however, only possible with intra-country panel data or by pooling countries—the latter yielding average acreage responses only.

Endnotes

[1]Data sources, including crop calendar information, can be found in a related publication in Haile et al. (2014).

[2]We have further inspected our data series for outliers, influential variables, leverages, multicollinearity, and normality. For instance, we have run several variable influence diagnostics including DFFITS and DFBETA to assess how much the estimated values of our dependent variables are influenced by a few observations or data points. These analyses result in as many plots as there are country-crop model specifications, which are not reported here for the sake of brevity. However, such plots for either all or selected country-crop model specifications can be available upon request.

[3]It is worth to note here that Hausman (2012) employs panel data analysis using county-level data from 1973 to 2005, whereas this study applies a time series analysis using data from 1991 to 2013.

Appendix

Table 8 Crop calendar information of seasonal crops

Country	Crop	J	F	M	A	M	J	J	A	S	O	N	D
Brazil	Corn – *safra*												
	Corn – *safrinha*												
China	Corn – *North*												
	Corn – *South*												
	Rice – *early crop*												
	Rice – *mid & late*												
	Rice – *double late*												
	Wheat – *Spring*												
	Wheat – *Winter*												
India	Rice – *kharif*												
	Rice – *rabi*												
	Corn –*kharif*												
	Corn – *rabi*												
			Planting						Harvesting				

Sources: FAO GIEWS, FAO-AMIS, and USDA. Refer to Haile et al. 2014 (AE Journal) for all remaining national crop calendar information

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Authors' contributions
MH conceived the study, drafted the manuscript, and performed part of the statistical analysis; JB performed part of the statistical analysis and wrote part of the manuscript; and MK contributed in developing the concept note and edited the manuscript. All authors read and approved the final manuscript.

Competing interests
We declare that we do not have any competing interests.

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References

Braulke M (1982) A note on the Nerlove model of agricultural supply response. Int Econ Rev 23(1):241–244

Chavas JP, Holt MT (1990) Acreage decisions under risk: the case of corn and soybeans. Am J Agric Econ 72(3):529–538
Coyle BT (1993) On modeling systems of crop acreage demands. J Agric Resour Econ 18(1):57–69
Economic Research Service (ERS) - USDA (2013a) Corn:trade. Available at http://www.ers.usda.gov/topics/crops/corn/trade.aspx. Accessed 14 July 2016.
Fama EF, French KR (1987) Commodity futures prices: some evidence on forecast power, premiums, and the theory of storage. J Bus 60(1):55–73
FAO. (1996). Rome Declaration on World Food Security and World Food Summit Plan of Action (pp. 13–17). World Food Summit: Rome, Italy.
FAO. (2012). Agricultural Statistics, FAOSTAT. FAO (Food and Agricultural Organization of the United Nations). Rome, Italy.
FAO, IFAD, & WFP. (2015). The State of Food Insecurity in the World 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress. Rome, Italy: Food and Agriculture Organization of the United Nations.
Foreign Agricultural Service (FAS) - USDA (2013b). Commodity intelligent report. Available at http://www.pecad.fas.usda.gov/highlights/2013/05/br_15may2013/. Accessed 14 July 2016.
Fuller W (1976) Introduce to statistical time series. Wiley, New York
Gardner BL (1976) Futures prices in supply analysis. Am J Agric Econ 58(1):81–84
Haile MG, Kalkuhl M, von Braun J (2014) Inter- and intra-seasonal crop acreage response to international food prices and implications of volatility. Agric Econ 45(6):693–710
Haile MG, Kalkuhl M, von Braun J (2015) Worldwide acreage and yield response to international price change and volatility: a dynamic panel data analysis for wheat, rice, corn, and soybeans. Am J Agric Econ 97(3):1–19
Hausman C (2012) Biofuels and land use change: sugarcane and soybean acreage response in Brazil. Environ Resour Econ 51(2):163–87
Hernandez, M, & Torero, M (2010) Examining the dynamic relationship between spot and future prices of agricultural commodities: IFPRI Discussion Paper 00988: International Food Policy ResearchInstitute (IFPRI), Washington DC.
Just, R E, & Pope, R D (2001) The agricultural producer: theory and statistical measurement Vol. 1. B. Gardner & G. Rausser (Eds.), Handbook of Agricultural Economics, pp. 629–741. North-Holland.
Liang Y, Corey M,J, Harri A, Coble KH (2011) Crop supply response under risk: impacts of emerging issues on Southeastern US agriculture. J Agric Appl Econ 43(2):181
Parry, M., Evans, A., Rosegrant, M. W., & Wheeler, T. (2009). Climate change and hunger: responding to the challenge. Rome, Italy: World Food Programme.
Trostle, R (2008) Global agricultural supply and demand: factors contributing to the recent increase in food commodity prices. USDA report. Available on http://www.ers.usda.gov/publications/wrs-internationalagriculture-and-trade-outlook/wrs-0801.aspx. Accessed 15 Oct 2015.
Wooldridge J (2009) Introductory econometrics: a modern approach, 4th edn. South-Western Cengage Learning, Mason
von Braun, J, & Tadesse, G (2012) Food security, commodity price volatility and the poor. In Masahiko Aoki, Timur Kuran & G. Roland (Eds.), Institutions and Comparative Economic Development: Palgrave Macmillan Publ. IAE Conference Volume 2012.

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