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Forecasting Potato and Sweetpotato Yields for 2050

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CIP-Lima

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Comments are invited.

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Abstract

This document presents a systematic method for validating the performance and improving the parametrization of IFPRI's International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT), the main quantitative tool in the Global Futures and Strategic Foresight project in which CIP has been participating since 2010. The validation of the model focuses on the world's ten largest producing countries for potato and sweetpotato and consists in reviewing parameters related to yield growth rates. Since the baseline for IMPACT is 2005, validation involves the assessment of the model's performance for both in-sample (using FAOSTAT reported yields until 2013) and out-of-sample forecasts (until 2050). In the first case, potato and sweetpotato yields are compared against FAOSTAT data using two different statistical measures of accuracy and appropriate critical values. Historical potato and sweetpotato yield time series from FAOSTAT are also used to build Auto-Regressive Integrated Moving Average (ARIMA) models for each country in order to estimate yields for 2050. The ARIMA forecasts and the respective yield trajectories produced by IMPACT are compared and then reviewed using literature sources, statistically estimated prediction intervals and practical rules of thumb.

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1. INTRODUCTION

Potato (Solanum tuberosum) and sweetpotato (Ipomoea batatas) are important staple crops and valuable marketed commodities in many parts of the world, especially in developing countries where their role in achieving nutritional security and providing income generation opportunities has been widely recognized. Potato is currently the world's principal non-grain crop in terms of human consumption and its importance in the global food system has been steadily increasing since its introduction to Europe in the 16th century. Furthermore, because of its high energy content and nutritional value, potato is regarded as a major component of strategies targeting at food security. At the same time, it is significantly less affected by the high volatility of food prices than cereals, as was shown in the 2007/2008 food price crisis (FAO, 2009) and can also provide opportunities for poverty alleviation when grown as a cash crop in areas that are possibly not suitable for grain crops (Brown and Kennedy, 2005). As a result of the above traits, potato systematically exhibits positive income elasticity of demand (Scott et al., 2000b) and has been the only root and tuber crop with consistent increases in per capita consumption over the past decades (Alexandratos and Bruinsma, 2012).

Potato is widely cultivated around the world, both in developed and developing countries (Table 1.1). In the former, human consumption of fresh potatoes has decreased but potato has found a new place in farmers' production plans as an important cash crop which can be sold in local markets or used as input by processing industries (Bohl and Johnson, 2010; EC, 2007).

Table 1.1: Global potato production information for 2011-2013

Country	Production (tons)	% of global production	Area harvested (ha)	% of global area
China	92,383,093	24.7%	5,525,590	28.6%
India	43,055,333	11.5%	1,920,800	9.9%
Russian Federation	30,804,375	8.2%	2,162,541	11.2%
Ukraine	23,252,267	6.2%	1,426,242	7.4%
United States	20,107,706	5.4%	439,880	2.3%
Germany	10,724,167	2.9%	246,600	1.3%
Bangladesh	8,378,286	2.2%	444,859	2.3%
Poland	7,874,267	2.1%	370,233	1.9%
Netherlands	6,966,697	1.9%	154,934	0.8%
France	6,918,675	1.8%	157,857	0.8%

Source: FAO (2015).

On the other hand, sweetpotato is a tropical root and vine crop which most probably originates from Central America (Zhang et al., 2000) and is now the 12th most important crop in terms of total dry weight production (FAO, 2015). Although the status of sweetpotato varies significantly across different countries, in most regions it is considered as a “poor mans’ crop”, suitable only for those who cannot afford a grain- and meat-based diet. This last characterization however does not give justice to the historical role of sweetpotato in promoting food security and relieving famine, especially when grown as a “safety” crop in times of natural disasters or adverse weather conditions (Loebenstein, 2009). Most importantly, the orange-fleshed sweetpotato 1varieties (OFSP) are regarded as an ideal food for combatting vitamin A deficiency (Hotz et al., 2012) which is one of the major health problems of undernourished populations in Asia and Sub-Saharan Africa (SSA). Furthermore, sweetpotato in most developing countries is a “dual-purpose” crop, typically found in small scale farming system, and grown primarily for human consumption and secondarily as livestock feed. Vines, in particular, are not marketed and can be used as a supplementary animal feed. This “dual-use” of sweetpotato has the potential of yielding higher profits than traditional grain crops used as food and feed (Claessens et al., 2009). Sweetpotato cultivation also has important gender implications since women play an important role in production and post-harvest activities, especially in African countries (Tewe et al., 2003).

Sweetpotato is grown in over 100 countries, but the bulk of production is concentrated in developing countries in Asia and SSA (Table 1.2). However, contrary to potato whose cultivation is spatially distributed more homogeneously across the globe, China almost monopolizes world production, accounting for about 70% of global output and 42% of total areas harvested.

Table 1.2: Global sweetpotato production information for 2011-2013

Country	Production (tons)	% of global production	Area harvested (ha)	% of global area
China	72,635,390	70.2%	3,404,247	41.9%
Nigeria	3,383,333	3.3%	1,111,667	13.7%
Tanzania	3,353,927	3.2%	712,964	8.8%
Uganda	2,595,567	2.5%	540,597	6.7%
Indonesia	2,355,410	2.3%	172,755	2.1%
Vietnam	1,380,957	1.3%	141,211	1.7%
United States	1,182,834	1.1%	49,844	0.6%
Madagascar	1,114,317	1.1%	154,333	1.9%
India	1,083,933	1.1%	111,800	1.4%
Rwanda	977,209	0.9%	108,917	1.3%

Source: FAO (2015).

Despite their importance in combating poverty and malnutrition, the literature on the future role of potato and sweetpotato in the global food system is very limited. Among the few known examples of such analyses are the CIP-IFPRI foresight studies (Scott et al., 2000a, b; Walker et al., 2011a) which are based on IFPRI's International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT). IMPACT is an annually recursive, partial equilibrium, global economic model which has been developed to investigate the effect of future climate and socioeconomic changes on the production, demand and trade of agricultural commodities at the global or regional level (Delgado et al., 1999; Pandya-Lorch and Rosegrant, 2000; Nelson et al., 2010; Jalloh et al., 2013). The model has also been used to examine specific issues related to the agricultural sectors, such as biofuels (Rosegrant et al., 2008) and water scarcity (Rosegrant and Cai, 2001). IMPACT is built with FAOSTAT data and in its current version it uses 2005 as the reference year (initial year simulated). It includes 56 commodities and 320 Food Production Units (FPUs), which are sub-national geospatial units that are produced by the intersection of 159 geopolitical regions (countries) and 154 hydrological basins.

IMPACT is also the main quantitative tool used by the Global Futures & Strategic Foresight (GFSF) initiative with which CIP has been engaging since 2010. CIP's aim is to improve the representation of potatoes and sweetpotatoes in IMPACT by reviewing and suggesting adjustments to the model's key parameters as part of the larger effort of GFSF in the direction of creating an integrated bio-economic foresight modeling framework that can be used for drawing valid conclusions and performing comparisons across a large number of crops and under different scenarios of future change.

Given its role as a projection model, the most important set of parameters in IMPACT are those which vary with time and simulate the future status for critical components of the socioeconomic and biophysical conditions that affect the annual demand-supply equilibrium for each agricultural commodity. One such set of parameters that stands out for its role in determining future crop productivity is the set of Intrinsic Productivity Growth Rates (IPRs) which can be interpreted as a non-price induced exogenous yield trend that represents a "baseline" or "business as usual" scenario of yield growth. Any factor that modifies – additively or multiplicatively – the initial IPR values, corresponds to a scenario of accelerated growth in yields (e.g. technological innovations from agricultural research). Note that the yield growth rates defined by the IPRs are not the final yields produced by IMPACT. More specifically, the yield equation for every land type k (irrigated or rain-fed), commodity c and FPU f can be expressed as:

$$Y_{c,f,k} = YInt_{c,f,k} \times YInt2_{c,f,k} \times YWat_{c,f,k} \times YClim_{c,f,k} \times \left(\frac{PNET_{c,cty}}{PNET0_{c,cty}} \right)^{Y\varepsilon}$$

where $YInt$ is the crop yield intercept (base year crop yield), $YInt2$ is the exogenous crop yield growth, $YWat$ is the exogenous yield shock from water stress, $YClim$ is the exogenous yield shock from climate change, $PNET$ is the current net price (incorporates the cost of inputs), $PNET0$ is the base year net price (used for price indexing), index cty denotes the country[1], whereas $Y\varepsilon$ represents the price response with respect to net price. All above yield parameters are defined for 5-year intervals (2005-2009, 2010-2014, etc.).

[1] The price parameters are country-specific and thus apply for all FPUs in the same country.

The IPRs correspond to parameter $YInt2$ and under the "baseline" scenario they define the exogenous annual change to crop yields which is not explicitly represented elsewhere the model. According to the IPR definition, $YInt2$ also includes the long term effect of climate on crop productivity, contrary to $YClim$ which represents deviations from the "expected" future climatic patterns. The "baseline" scenario in IMPACT ignores the effect of climate shocks and water stress on crop yields and so the $YWat$ and $YClim$ parameters can be thought of having a value of unity.

Since IPRs constitute critical parameters that greatly affect the results obtained for key output variables, it is necessary to ensure that the productivity growth they simulate is in line with current scientific estimates about future yields. The objective of this exercise is therefore to review and suggest changes to the IPRs for potatoes and sweetpotatoes in order to improve the model's baseline projections. For this purpose, we focus on analyzing future yield growth trends for the ten largest producing countries in each crop, as shown in Tables 1.1 and 1.2. Although most of them, especially in the case of potatoes, do not constitute "target" countries for CIP (CIP, 2013), their high production volumes can affect the aggregate supply and consumption patterns and consequently determine the global price equilibrium, as this is modeled by IMPACT. Thus, from a modeling perspective, for this exercise there is scope in focusing on countries that are able to affect world prices through the simulated trade flows in the model, contrary to smaller producers who are considered to be "price-takers" in the sense that shifts in their supply curves have a negligible impact on market equilibrium.

2. METHODOLOGY

2.1. Methods of yield Forecasting

The increasing or decreasing trends in crop yields, as captured by the IPR values in IMPACT, are the combined outcome of different factors like climate, the improvement or deterioration of existing infrastructure, farmers' access to resources, and finally agricultural research which leads to increased productivity through higher yielding varieties or cultivars which are resistant to biotic and abiotic stresses. It is thus obvious that the projection of future crop yields is an extremely difficult task because it is not possible to account for all the factors that may affect crop productivity. Furthermore, the lack of appropriate data makes it is sometimes very difficult to ensure that a causal effect on yield trends actually exists since many factors seem to work towards opposite directions and are also subject to great uncertainty themselves. For example, it is possible that climate change will have a positive effect on potato yields in certain areas in the world, but will also increase the stress from biotic factors and will consequently result in higher probability of yield losses (Haverkort and Verhagen, 2008).

As a result of the above difficulties, the typical non-price determinants of yield growth which are considered in projection studies are GDP per capita, climate and technological change (Choi and Helmberger, 1993; Kaufmann and Snell, 1997; Ewert et al., 2005; Müller and Robertson, 2014; Havlík et al., 2014). On the other hand, the effect of the non-price and non-climate components on historical yield trends (e.g., public and private research, agricultural extension, markets and infrastructure) has not received much attention in the literature, again due to the lack of appropriate information and the complexity of modeling such causal relationships. To the extent of our knowledge, the projections of rice yield in India for 2020 by Evenson and Rosegrant (1995) is the only study that attempts to analyze the effect of the non-price and non-climate supply components on yield growth. The method used by the authors was based on the weighted extrapolation of yield trends estimated from historical data. The weights were applied for every five-year interval (1990-95, 1996-2000, etc.) and were derived from the decomposition of yields into components and subcomponents, while their effect on the yield trends was estimated based on a mix of expert opinion and literature review.

Expert opinion is in fact another alternative to yield trend projection. The best known examples in the literature are the FAO studies on the future of food and agriculture that rely on the judgment from specialists around the world for an initial estimate of yield and land trends (Alexandratos, 1995; Bruinsma, 2003). Like in IMPACT, these trends are used as inputs in the price equilibrium model FWFM (FAO World Food Model) which produces a final set of estimates. As argued by Evenson and Rosegrant (1995), "*expert-based projections have the merit that they reflect expert opinion, not only about total supply trends but to at least some degree about sub-components of these supply trends as well*". However, the criteria and assumptions used by specialists cannot be formally described and they can vary from one person to another and over time (Alexandratos, 1995).

The above problems in the estimation of non-price components of yield growth imply that the only feasible way to ensure a valid parameterization of IMPACT is to manually or automatically adjust the IPRs so that the model reproduces a plausible "business as usual" scenario of future yield growth. Therefore, the practical objective of this paper is not the estimation of the IPRs themselves but the definition of such a scenario. An obvious starting point for achieving this objective is the statistical analysis of historical yield time series for forecasting future yield trends. The literature lists a significant number of studies that attempt to identify yield trends for major crops across the globe (mainly cereals) by fitting polynomial trend models to historical yield data (e.g. Tweeten, 1998; Reilly and Fuglie, 1998; Dyson, 1999; Hafner, 2003; Jaggard et al., 2010; Grassini et al., 2013; Ray et al., 2013).

With few exceptions, however, polynomial trend models have been mostly used for descriptive purposes but very seldom for actual forecasting. Moreover, to the extent of our knowledge, the only study that has attempted to forecast potato yields at the global scale using historical data is Jaggard et al. (2010) who estimated linear trend models in different countries and adjusted their projections for 2050 to simulate different growth scenarios. On the contrary, the most popular approach for forecasting future values of a univariate time series is to assume that the series is generated by an Autoregressive Integrated Moving Average (ARIMA) process. ARIMA modeling is very popular in engineering and finance but has also been used in numerous applications in the field of agricultural economics. For example, Harris et al. (2012) modeled coffee production in Ghana, Badmus and Ariyo (2011) examined future maize production in Nigeria, Biswas and

Bhattacharyya (2013) forecast area and production of rice in West Bengal, while Verma et al. (2012) studied the yield trends of nine crops in Germany. All of the above studies performed short term forecasting of future (out-of-sample) yields with the exception of Badmus and Ariyo (2011) who projected maize yields for 38 years ahead. Biswas and Bhattacharyya (2013) and Verma et al. (2012) also examined the validity of their estimated ARIMA models by evaluating the accuracy of in-sample forecasts. Other studies using ARIMA models include, among others, Bessler (1982) who examined the relationship between an adaptive expectations model and moving average processes, Goodwin and Ker (1998) who created distributions of two year-ahead yield forecasts in order to determine premium rates for contracts in group risk farm programs in the United States, and Harri et al. (2009) who used ARIMA with the objective to test the hypothesis of normality in crop yield distributions.

In this paper we perform a similar type of analysis and we use ARIMA modeling to forecast potato and sweetpotato yields for 2050 in the world's ten largest producing countries. The data used for this exercise comes from FAOSTAT and covers the years 1961-2013. The yield series for each country and crop has been split into a "training" sub-sample (1961-2010), which is used for the estimation of the ARIMA models, and a "test" sub-sample (2011-2013) for the short-term in-sample evaluation of the ARIMA forecasts. Since the current version of IMPACT is also built with FAOSTAT data and uses 2005 as the reference year, we examine the model's projections for the period 2005-2013 and we suggest calibrating adjustments to existing IPRs where needed. Although the goal of calibrating IMPACT is to capture the existing trend rather than to accurately reproduce observed yields, we will propose corrections not only regarding the slope of the yield trajectories but also for adjusting absolute yield levels for 2005-2013 when we deem that the discrepancy between observed and forecast values is important. Finally, the out-of-sample ARIMA forecasts (for 2050) and the respective yield trajectories produced by the existing IPR values in IMPACT are compared and reviewed using literature sources, statistically estimated prediction intervals and practical rules of thumb.

2.2. The forecasting model

The initial step to building a forecasting model is to detect and correct the time series for outliers, i.e., non-repeatable observations that may result in biased parameter estimates. The outliers considered in this paper are: additive outliers (AO – extremes that do not affect following values in the time series); temporary changes (TC – effects that gradually disappear with time); and level shifts (LS – a sudden permanent change in the series, which when not accounted for may be misinterpreted as evidence of a unit root). The method employed for detecting outliers is based on the iterative procedure by Chen and Liu (1993). For completeness, we start the presentation with the autoregressive moving average (ARMA) model which can be written in simple form as:

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

where y_{t-p} are autoregressive terms up to order p, and ε_{t-q} are errors of lag q with a zero mean and constant variance (white noise). With the lag operator $By_t = y_{t-1}$ and $B\varepsilon_t = \varepsilon_{t-1}$ the previous equation can be written more succinctly as:

$$\varphi(B)\mathrm{y}_t = \theta(B)\varepsilon_t \quad (2)$$

where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ are polynomials of B of order p and q respectively, whose unit roots lie outside the unit circle (that is, $|\varphi_i| < 1$ and $|\theta_m| < 1$ for all $i \in p$ and $m \in q$). By differencing model (2) d times we obtain an $I(d)$ model – integrated of order d – which is known as an ARIMA (p,d,q):

$$\varphi(B)(1 - B^d) y_t = \theta(B)\varepsilon_t \quad (3)$$

Model (3) can also be written as:

$$y_t = \frac{\theta(B)}{\varphi(B)\alpha(B)} \varepsilon_t \quad (4)$$

where $\alpha(B)$ is a polynomial of B of order d whose roots are on the unit circle such that $(1 - B^d) y_t = \alpha(B)$.

The outlier detection method by Chen and Liu (1993) is based on a given ARIMA model, expressed as in equation (4), and comprises three stages:

(I) In the first stage, s potential outliers are detected by examining the residuals $\hat{u}_t$ obtained from fitting the given ARIMA model to the time series under investigation:

$$\hat{u}_t = \sum_s \omega_s \pi(B) F_s(B) I_t(t_s) + \varepsilon_t \quad (5)$$

where $I_t(t_s)=1$ if an outlier is found at point $t=t_s$ and 0 otherwise, $F(B)$ is the dynamic pattern of the outlier, ω its magnitude and $\pi(B)=\varphi(B)\alpha(B)/\theta(\mathrm{B})$ is the weighting polynomial $1-\pi_1 B-\pi_2 B^2-\ldots-\pi_s B^s$ whose π_s coefficients vanish to zero as the number of outliers m becomes very large. $F(B)$ takes a value of 1 for an AO, and is equal to $1/(1-\delta B)$ for a TC and an LS. Parameter δ is equal to 1 for an LS outlier type, whereas Chen and Liu (1993) recommend a value of 0.7 for a TC.

The magnitude ω of a potential outlier is estimated with equation (5) using least squares. If the existence of an outlier is known at time t_s then this initial regression uses a sub-sample $t_s,\ldots,n$ from a total of s observations in the time series. When the existence of an outlier is not known a priori, a series of regressions is performed for all points (sub samples) between $t=1$ and $t=n-1$ and the standardized statistic of ω for the different outlier types at each point t is calculated (inner loop). If this statistic is higher than a predetermined critical value, which is defined as a function of sample size, then this point is an outlier.

(II) In the second stage, the effects of the s outliers identified at stage I are jointly re-estimated using equation (5). If the new standardized estimate of each ω_s is lower than the previously defined critical value then the outlier is ignored, otherwise its effect is removed and the following intervention ARIMA model is estimated:

$$y_t^* = y_t + \sum_s \omega_s F_s(B) I_t(t_s) \tag{6}$$

where the interventions (dummy variables) are defined as $\omega_s F_s(B) I_t(t_s)$ for all points t_s. If the relative change of the residual standard error is smaller than 0.001 compared to the initial ARIMA estimate at stage I, then the outlier effects are jointly estimated again using the new residuals produced from (6) as the dependent variable, otherwise the procedure moves to stage III.

(III) The information on the ARIMA parameters obtained from the estimated intervention model (6) in the previous stage is used to re-initiate the procedure (outer loop). The procedure is terminated when a (user-defined) maximum number of iterations is reached or when no more residuals are identified.

Outlier detection with the previous method is performed automatically with the "tso" command of the "tsoutliers" package in R. The package also provides the option to test iteratively a large number of ARIMA model specifications by implementing the "auto.arima" command from the "forecast" package (Hyndman and Khandakar, 2008) and proposes the one which returns the lowest value of a predefined information criterion. The use of an information criterion for selecting the appropriate number of AR and MA lags is probably the most commonly used approach for specifying an ARIMA model. We opt for the bias corrected version of the Akaike Information Criterion (AICC) which is proposed in the literature as the major criterion for selecting ARMA models (Brockwell and Davis, 2002):

$$\mathrm{AICC} = -2\ln L\left[\mathbf{v}_p, \mathbf{w}_q, \sigma^2(\mathbf{v}_p, \mathbf{w}_q)\right] + \frac{2n(p+q+1)}{n-p-q-2}$$

where $L(\cdot)$ is the likelihood of the parameter vectors $\mathbf{v}$ and $\mathbf{w}$ of an AR(p) and an MA(q) process respectively, σ^2 is the variance of the white noise (residuals) which also depends on $\mathbf{v}$ and $\mathbf{w}$ and n is the sample size. The likelihood function expresses the probability of obtaining a specific set of parameters given a certain model and the second term penalizes large order models, while also accounting for sample size.

A more traditional approach to model specification is the Box-Jenkins method which relies on examining the shape of the correlogram of the stationary time series. However, the Box-Jenkins method is not easy to implement because the correlogram may be difficult to interpret.

The "auto.arima" command also includes a test for stationarity which determines the order of differencing of the selected model. Two types of tests can be found in the literature depending on the null hypothesis they employ, i.e., existence of a unit root (non-stationarity) or stationarity. The most popular test belonging to the first category is the (Augmented) Dickey-Fuller (ADF – Dickey and Fuller, 1979), while the KPSS introduced by Kwiatkowski et al. (1992, an acronym of the authors' names) is probably the best known test that uses a null hypothesis of stationarity. Although widely used, unit root tests like the ADF are criticized for having relatively low statistical power (high probability of Type II error – failure to reject a false null hypothesis). This problem stems from the question of whether any deterministic terms (a constant and/or a linear trend) should be included in the test. The difficulty in choosing the right test equation has led to the development of various testing strategies (e.g. Elder and Kennedy, 2001; Enders, 2004; Pfaff, 2008). Similarly, the KPSS test equation may be specified in two ways: as a test for stationarity around a level (variance and mean remain constant over time) or around a linear trend (only the mean changes over time). The choice between the two tests depends primarily on the research question. For the purposes of the present analysis and since we are not explicitly searching for a unit root, we will rely on the KPSS test which seems to be the most popular test for series exhibiting a trend (like yields). Furthermore, Pfaff (2008) argues that it addresses the hypothesis specification more correctly from the viewpoint of conservative testing.

Once the model has been selected, the residuals need to be checked for zero autocorrelation; if they are correlated then further information can be extracted from them. Autocorrelation can be determined by looking at the correlogram in order to examine whether the autocorrelation coefficients at various lags are statistically significant. A more formal test that uses a single statistic is the so-called "portemanteau" test, or Ljung-Box statistic, which is based on the first h residual autocorrelations under the null hypothesis of independent errors. The only practical advice found in the literature with regards to the appropriate number of lags for the Ljung-Box test is given by Hyndman and Athanasopoulos (2013) who suggest using $h=10$ for non-seasonal data, based on considerations on the power of the test. The Ljung-Box test is carried out with the "Box.test" command of the "forecast" package in R.

We examine if the residuals are normally distributed by employing a formal Jarque-Berra test and also by inspecting the resulting QQ-plots. We need to note at this point that the Jarque-Bera test suffers from low statistical power when the sample is small ($n<50$), yet it still outperforms all similar tests for that sample size (Frain, 2007). Furthermore, although there are statistical reasons for requiring normality of the residuals, empirical research has failed to provide a definitive answer to whether the stochastic component of crop yields (errors) can be modeled as being normally distributed; a large number of studies in fact reject the hypothesis of a normal yield distribution (e.g. Moss and Shonkwiler, 1993; Ramirez et al., 2003; Harri et al., 2009). For these two reasons, residual normality is used as a supplementary diagnostic test which confirms the validity of a selected model but not as definite requirement. Nevertheless, as will be discussed in the results in the next section, there was only one instance where the hypothesis of normally distributed residuals was systematically rejected (sweetpotato in Uganda).

A complete summary of the estimated models in each country and a descriptive presentation of the outliers and their effect on the yield series is given in the appendix.

2.3. Forecasting accuracy

After estimation, the ARIMA model is used to produce in- and out-of-sample yield forecasts. For the evaluation of the in-sample ARIMA forecasts (i.e., 2011-2013) and the yields produced by IMPACT for the period 2005-2013, an accuracy measure is required. A very commonly used scale-independent measure for univariate time series forecasting is the Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

Since IPRs are defined in five-year intervals, we calculate different MAPE scores for 2005-2009 and for 2010-2013. We also define a MAPE threshold value of 7.5% as an indication of whether the existing IPRs in IMPACT need to be adjusted to better approximate reported yields. This value may seem arbitrary but it follows the reasoning found in the literature of evaluating mathematical programming (MP) agricultural sector models: static MP models are evaluated by examining the level of fit against observed values, usually with the Percentage Absolute Deviation (PAD) measure which can be seen as the multivariate, single year equivalent of the MAPE. In this framework, Hazell and Norton (1986) consider a PAD of 5% or less to be exceptional while they suggest adjustments to an MP model for PAD scores higher than 15%. The MAPE threshold we propose for IMPACT is half of the previous PAD value because the adjustment of IPRs is easier and more straightforward than the calibration methods used in MP models. Furthermore, the calibration requirements for recursive models are higher than for static ones since discrepancies in one period result in erroneous starting points for simulating the following periods.

Note that despite its name, the MAPE has been criticized for being biased when the denominator is small (as is the case with sweetpotato yields in some countries) and thus it is not independent of the scale of measurement. Moreover, extreme values, like yield surges that deviate from an assumed trend increase the MAPE and may wrongly suggest the need for model calibration. For this reason, we complement the MAPE with the Mean Absolute Scaled Error (MASE) which has been proposed by Hyndman and Koehler (2006) as an alternative, scale-independent measure of forecasting accuracy. It can be expressed mathematically as:

$$\text{MASE} = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|y_t - \hat{y}_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|y_t - y_{t-1}|}\right)$$

where the denominator is the average forecast error of the "naive" forecast method (i.e., the forecast in one period is equal to the value of the previous period).

The intuition behind the MASE is that it will be less than unity if the forecast is better than the simple "naive method" and greater than one if the forecast is worse. In this sense the MASE is not really a measure of fit but rather represents the opportunity cost of using elaborate models compared to the simplest possible forecasting method. However, a large average error of the "naive method" which leads to a MASE score of less than unity is also an indication of a highly volatile series. We therefore suggest adjustments to IPRs only when MAPE > 7.5% and MASE > 1; if IMPACT does not approximate well the recorded FAOSTAT yields, but it is more accurate than the naive method, then the low accuracy of the model can be attributed to the high volatility of the series and not to an erroneous parameter. An exception to this ad-hoc rule is when the yields forecast by IMPACT for an entire 5-year period are moving towards the opposite directions than what is observed in the series (growth vs. decline). In this case it is obvious that the MAPE will be large and IPR adjustments will be proposed regardless of the MASE score.

On the contrary, because of the pervasive nature of out-of-sample forecasting, no accuracy measure can be employed for the evaluation of ARIMA and IMPACT yield projections. For this reason, and as stated previously, we rely on the literature in order to identify estimates of future yield growth, or evidence which may suggest specific growth trajectories. Potato yield projections, in particular, are compared with those of Jaggard et al. (2010) which is the only known example of using historical data to forecast future potato yields. More generally, the literature review focuses on factors that are expected to affect future yield growth, such as demand potential, the impact of climate, research prospects for breeding and the development of improved varieties, and political objectives for increasing productivity. Our treatment of how these factors can impact future yields is not exhaustive; instead we attempt a rapid assessment of the most likely pathway of change with the aim to improve the validity of future simulations with IMPACT.

When the literature does not provide enough information for inferring a possible yield growth trajectory, we use a simple rule of thumb that relies on the 95% prediction intervals, which are produced with the accuracy command of the forecast package in R. More specifically, when the final yields in 2050 projected by IMPACT lie outside the ARIMA prediction interval, we propose IPR adjustments so that the model reproduces a "middle-road" scenario of yield growth, i.e., an average of the two forecasts. On the contrary, no adjustments are proposed when the IMPACT yield projections lie inside the prediction interval.

A summary of the results for in- and out-of-sample forecasts, including calculated Compound Annual Growth Rates (CAGRs) for the yield projections produced by both the ARIMA models and IMPACT is given in the appendix.

3. POTATO YIELD FORECASTS FOR 2050

The evolution of potato yields for the ten largest potato producing countries since 1961 is presented in Figure 3.1. Note that for Russia and Ukraine the series begins in 1992, that is, after the collapse of the Soviet Union.

Figure 3.1. Potato yields in the world's largest producing countries.

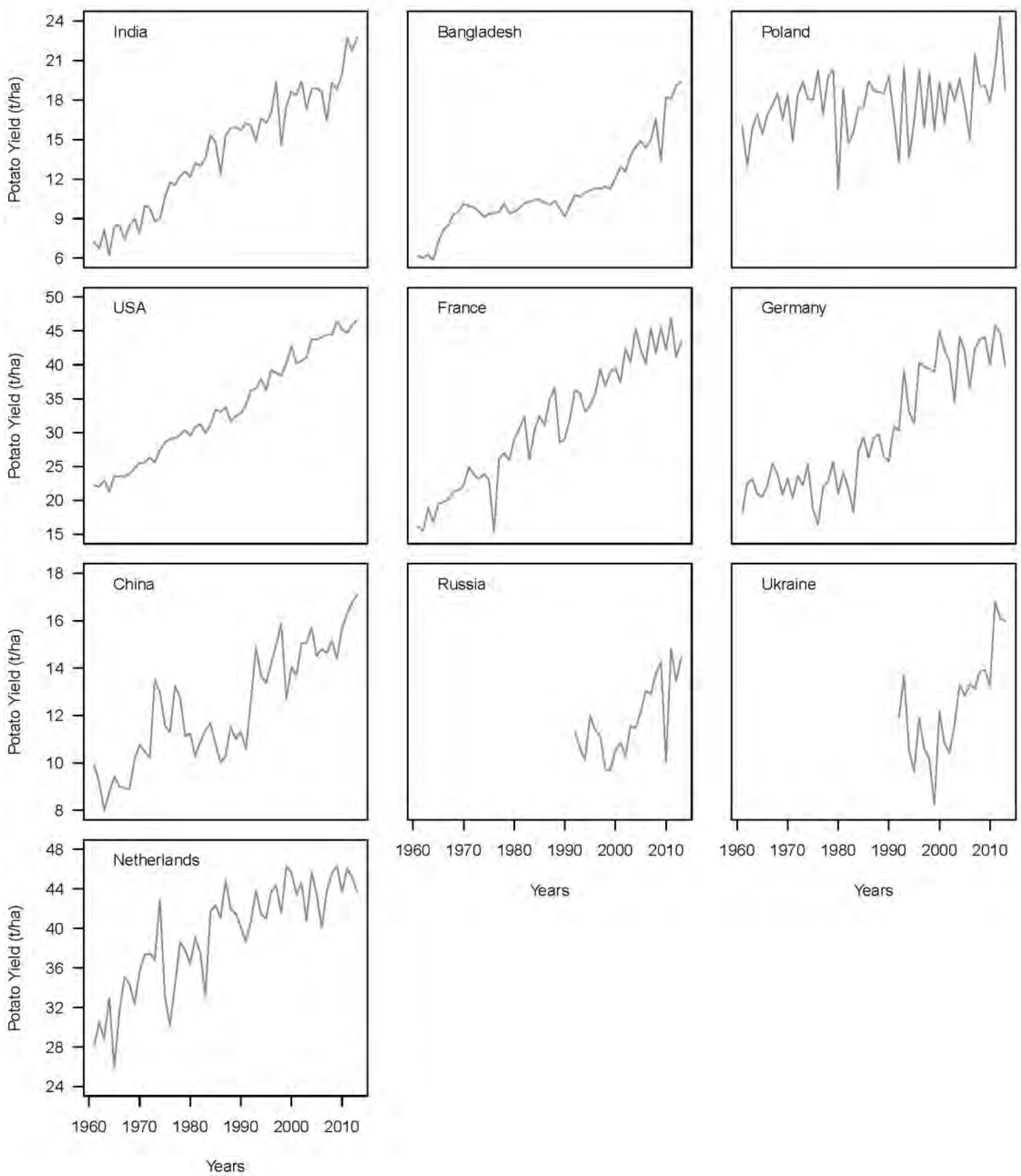


Figure 3.1 reveals that there exists a big difference in yields between developing and developed countries (western European and the US). This difference seems to be the combined effect of technical, institutional and climatic factors which affect both "attainable" and "actual" yields. The former can be defined as the maximum yield obtained from a specific cultivar in a given region under average environmental conditions using the best planting material and all the available technologies to minimize biotic and abiotic stresses. For example, it has been suggested that attainable potato yields in the tropics and sub-tropics are lower than in temperate climates because of shorter growing seasons and high temperatures which reduce photosynthesis and decrease the amount of intercepted radiation. In this case, breeding for cultivars which are better adapted to a specific locale could push attainable yields upwards (Bradshaw, 2009).

On the other hand, actual yields are the ones reported in statistical databases and are lower than attainable ones because of partial use of available technologies (e.g., inefficient use of resources), weather extremes, post-harvest losses, and pest and disease outbreaks. Low seed quality is probably the major technical factor responsible for the gap between attainable and actual yields (Haverkort and Struik, 2015) and together with biotic stresses (losses from viruses, bacterial wilt and late blight) it is ranked as one of the most important problems facing potato growers in developing countries (Fuglie, 2007a). Finally, the structure of the agricultural sector itself also plays an important role in determining actual yields: developed countries are characterized by a mechanized agricultural sector with large farming enterprises and cooperations which are able achieve economies of scale in production for their member farms. There is also sufficient access to capital and insurance schemes, intensive production techniques are applied involving sustainable use of chemical fertilizers, pesticides and irrigation. In contrast, the average farm in developing countries is smaller, with limited access to markets, while production often aims at satisfying the nutritional requirements of the household. In turn, this means that the production technology is less efficient with non-optimal use of inputs which may give rise to environmental problems, like soil degradation, and lead to even lower yields. Finally, higher post-harvest losses in small-scale farming could be caused by the lack of appropriate storage facilities (Pandey, 2007).

3.1. China

China has been the world's largest potato producer since 1993 and currently accounts for almost one quarter of global potato production and about 28% of total cultivated areas (FAO, 2015). Potato in China is mainly used for food, both as a fresh vegetable or in processed forms, while a smaller part is also utilized as animal feed (Scott and Suarez, 2012a). It is primarily grown in smallholder farms in many parts of the country with different production techniques under various agro-ecological conditions, and consequently displays high spatial yield variability (CIP, 2006). In average, potato yields in China have increased significantly during the last decades, rising from 10 tons per ha in 1961 to more than 16 tons per ha in 2013. This increase is particularly evident during the 90's, with a level shift detected in 1993 which can be attributed to the economic reforms that focused on a more liberal and market-oriented economic system. The analysis of the time series for China also revealed two temporary changes in 1973 and 1977 and an additive outlier in 1999. The occurrence of these outliers cannot be related to any significant event in the literature, but the two temporary changes in 1973 and 1977 are most probably the result of data quality problems caused by the dismantling of the Chinese statistical service in the 70's (Scott and Suarez, 2012b). The intervention model selected to describe the evolution of potato yields in China is an ARIMA(3,1,0) with a drift.

$$\begin{aligned}\hat{y}_t - y_{t-1} &= 0.074 - 0.359y_{t-1} - 0.338y_{t-2} - 0.658y_{t-3} + 3.466TC_{1973} + 2.394TC_{1977} \\ &\quad + 2.462LS_{1993} - 1.888AO_{1999} + \varepsilon_t\end{aligned}$$

IMPACT approximates reported yields for 2005-2009 adequately but it cannot capture the rapid productivity growth reported during the last years of the series. This means that the IPRs for the period 2010-2014 should be adjusted upwards.

Both IMPACT and the ARIMA model forecast the same yield trajectory until 2030, after which the former produces a declining yield trend, whereas the latter forecasts a steady yield growth resulting in 18.2 tons per ha in 2050 (Figure 3.2). Note that potato yield projections by Jaggard et al. (2010) for 2050 under a conservative growth scenario are much higher than the ARIMA projections (around 23 tons per ha). Nevertheless, given the objective of the Chinese government to double potato harvested areas by 2020, the growth rate projections (slope) by both models until 2030 are indeed likely to be realized. Climate change and increased CO_2 emissions are also expected to have a positive overall impact on potato yields in China despite the possible water pressures (World Potato Markets, 2015). At the same time, research on potato breeding is starting to focus not only on higher-yielding varieties, but also on improving traits and resistance to pests and diseases which may reduce the existing yield gap and strengthen the links with the processing industries (Jansky et al., 2007). The link with the industry and the great domestic demand potential for both french fries and fresh potatoes may also play an important role towards future potato productivity growth in China (Wang and Zhang, 2010; Scott and Suarez, 2012a). Walker et al. (2011a) argue that developing countries have not been able thus far to establish themselves as important players in the global trade of french fries, which is currently dominated by Canada, the United States and the Netherlands. China is currently a net, albeit small, importer of french fries but given the size of the domestic market and the continuous output growth, future changes in the global markets of processed potato products are very difficult to predict (Wang and Zhang, 2010).

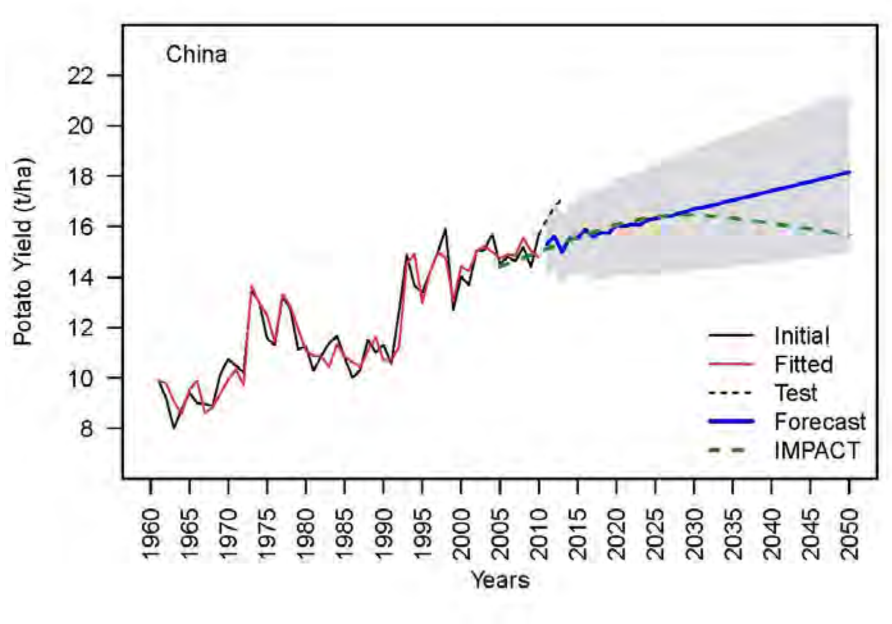


Figure 3.2. Potato yield forecast for China.

All previous factors may be summarized in a likely future annual growth rate of around 1.75-2% of potato production in China, as suggested by various sources (e.g. Scott and Suarez, 2012b; Walker et al., 2011a). Since output growth in China has been traditionally driven by the expansion of cultivated area, the moderate yield growth (CAGR of 0.51%) produced by the ARIMA model seems reasonable because it may become difficult to improve productivity over a constantly increasing land area under cultivation. However, given that FAOSTAT reports yields of 15.3 tons per ha in 2013 and that China has been revising its national statistics regarding potato production (Scott and Suarez, 2012b), yields of over 20 tons are also possible.

3.2. India

After an impressive increase in output over the last five decades, India is currently the world's second largest potato producer with an estimated supply of more than 45 million tons in 2013 (FAO, 2015). Potato in India is mainly grown in the Indo-Gangetic plain, either as monoculture or in rotation with maize, wheat and/or rice and it is regarded as both an important staple and a cash crop (CIP, 2006). Following the growth in production volumes, potato yields in India have also increased significantly as a result of successful breeding programs, a quality seed system and storage infrastructure that have reduced post-harvest losses (Scott and Suarez, 2012c). The potato yield series for India contains two additive outliers in 1998 and 2007 and the intervention model selected was an ARIMA(0,1,1) with a drift.

$$\hat{y}_t - y_{t-1} = 0.267 - 3.071AO_{1998} - 2.807AO_{2007} + \varepsilon_t - 0.759\varepsilon_{t-1}$$

As in the case of China, IMPACT does not capture the yield growth reported in 2010-2013 and therefore the IPRs for that period should be adjusted upwards. Regarding out-of-sample forecasts, the ARIMA model suggests steadily increasing yields so that the national average reaches 30 tons per ha in 2050 (Figure 3.3). Such yield levels, which are also forecast by Jaggard et al. (2010) under a conservative growth scenario, are not uncommon in the Indo-Gangetic plain. However, they have been exhibited for only a limited duration probably due low factor productivity and the existence of a yield plateau (Walker et al., 2011a). Bradshaw (2009) also argues that with early tuber initiation and rapid bulking yields in the Indo-Gangetic plain can even surpass 40 tons per ha. Moreover, national breeding programs have already produced varieties with high attainable yields (30-40 tons per ha) but these are targeted towards the processing industry which presently accounts for only 4% of total potato production in the country (Pandey et al., 2009). Future yields in India are also expected to be significantly impacted by climate change, but adaptation and new heat- and drought- tolerant varieties can mitigate this effect and may even lead to limited productivity growth (Naresh Kumar et al., 2015).

The continuously rising demand for potatoes due to increases in income, especially in urban areas, has already been suggested as the main reason behind the output growth during the last decades. Given that potato consumption in the country is currently lower than in other parts of Asia, and that India is predominantly a vegetarian culture, further increases in income are likely to result in higher consumption levels for potato and they may also lead to investments in the processing industry which is currently under-exploited (Scott and Suarez, 2011). At the same time, the rising Indian population will set significant challenges for food and nutritional security, especially in rural areas, and will possibly be another driver of future productivity growth. This is affirmed by the ambitious objective set by the Indian government to achieve yields of 34.5 tons per ha in 2050 and to promote higher levels of potato consumption per capita (World Potato Markets, 2015). From the previous discussion we consider the forecast of 30 tons per ha in 2050 produced by the ARIMA model to be a reasonable scenario of yield growth.

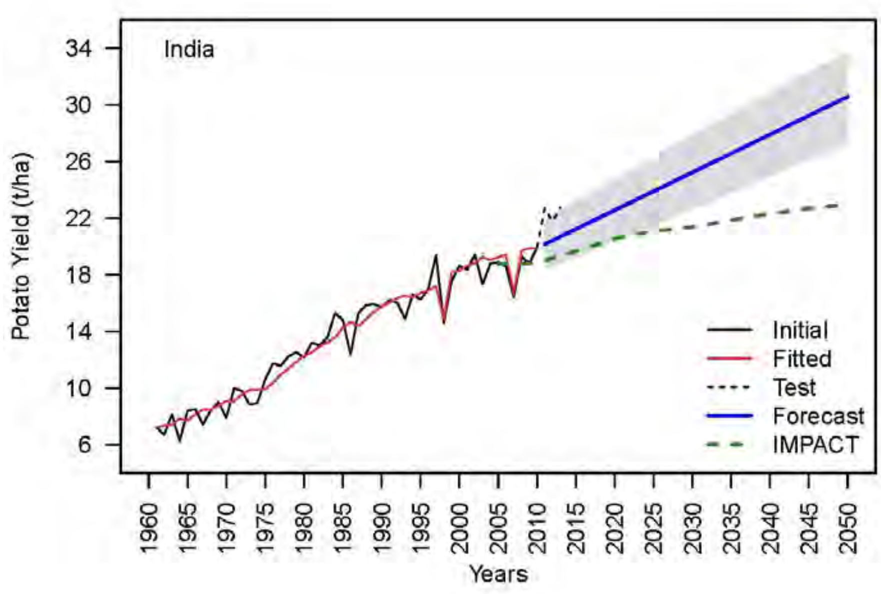


Figure 3.3. Potato yield forecast for India.

3.3. Russia and Ukraine

Russia and Ukraine are special cases because the available observations do not suffice for a complete characterization of the evolution of yields as an ARIMA process (the series starts in 1992 and therefore includes 22 years in total). For this reason, instead of ARIMA we estimate linear models for the entire 1992-2013 series.

Starting with Russia, the first visual observation is that the 2010 yield probably constitutes an outlier. Indeed, additional research revealed that this low yield value is the result of wildfires which lasted for about two months and destroyed a large part of the country's agricultural production (Parfitt, 2010). A dummy variable for 2010 is used to correct for the outlier effect on the estimation process. Both the time trend and the dummy variable were found to be statistically significant at the 5% level. Furthermore, the Breusch-Pagan did not reject the hypothesis of homoscedastic residuals and the Jarque-Berra test found no evidence against the residuals being normally distributed. However, the Breusch-Godfrey test revealed the existence of first order residual autocorrelation. To account for autocorrelation we estimated a linear model with heteroscedasticity- and autocorrelation-consistent standard errors:

$$\hat{y}_t = 9.677 + 192t - 3.419AO_{2010}$$

IMPACT produces an almost horizontal yield trend after 2010, whereas it is evident that potato yields in the country have been growing since the beginning of the century. This is confirmed by the linear trend model which has estimated an annual increase of around 0.2 tons per ha for the sample period. Furthermore, the extrapolation of the linear trend suggests that potato yields in Russia will reach around 22 tons per ha in 2050 (Figure 3.4). This yield level is comparable to the 2050 yields forecast by Jaggard et al. (2010) under a "business as usual" scenario (21 tons per ha).

The reason for the currently low yields in Russia is that potato production in the country is still predominantly a household activity, while production in larger farm enterprises with investments in modern equipment and new agro-economic practices has started to increase only recently, and has been the main driver behind the upward yield trend which started after 2000 (Vassilieva, 2013).

However, existing research for improving seed quality (Simakov et al., 2008) and the projected positive effects of climate change on potato yields in Russia, assuming that farmers follow appropriate adaptation strategies (Hijmans, 2003), suggest that yields will most likely continue to increase in the future. Hence the extrapolation of the estimated linear trend seems to be a reasonable scenario for potato yields in Russia

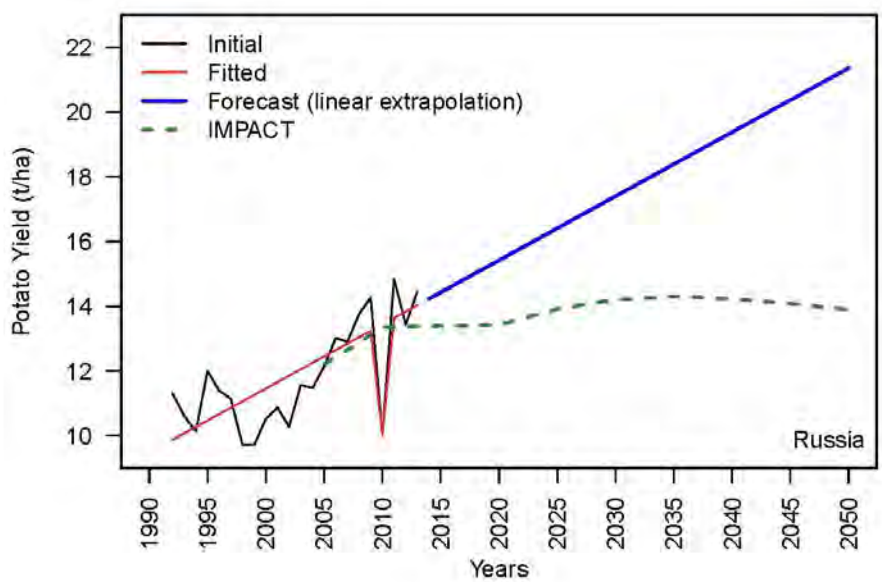


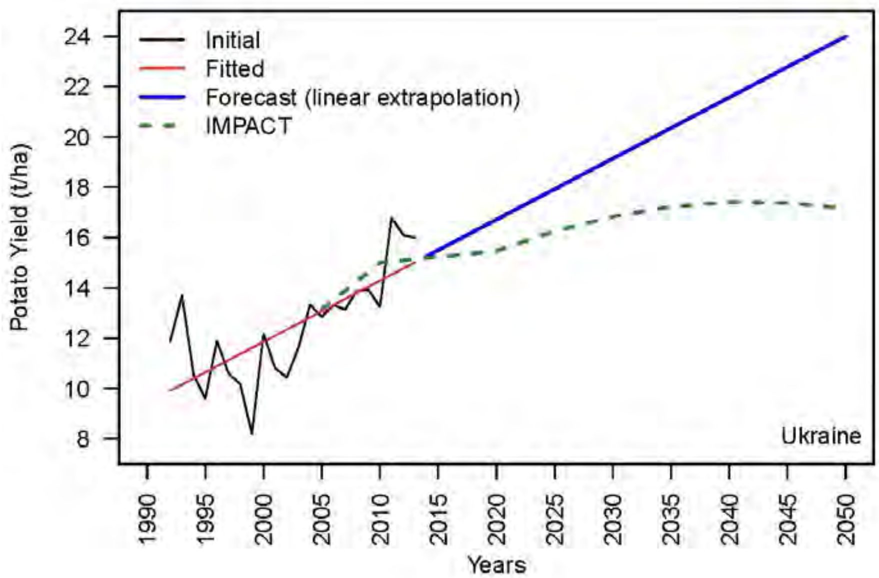
Figure 3.4.
Potato yield forecast for Russia.

Regarding Ukraine, the linear trend model for potato yields was estimated with Ordinary Least Squares and the residuals were found to be independent and identically distributed $N(0,\sigma^2)$:

$$\hat{y}_t = 9.674 + 0.243t$$

The extrapolation of the linear trend in Ukraine leads to an average national potato yield of around 24 tons per ha by 2050 (Figure 3.5). Although this yield is technically feasible, recent political events and the civil war in the country will probably prove a serious obstacle to achieving this objective. Hence, the leveling of yields at 17 tons per ha after 2010 in the IMPACT model is a rather reasonable scenario, given the uncertainty brought about by war.

Figure 3.5. Potato yield forecast for Ukraine.



3.4. United States

The United States are the fifth largest potato producer in the world with more than 420,000 hectares harvested in 2013 and a total output of almost 20 million tons (FAO, 2015). Although in the United States potato is no longer the nutritional staple of the past, it is nevertheless gaining increased appreciation by nutritionists because of its nutrient density and its contribution to a more balanced diet (Bohl and Johnson, 2010). Furthermore, there is a large demand by the processing industry which produces commodities like frozen French fries and chips for both the local and foreign markets, generating significant income streams for the involved farm enterprises.

Potato yields in the United States have grown almost linearly since 1961 and currently exceed 46 tons per ha. The analysis for the yield series revealed a temporary change in 1988 and an additive outlier in 2000. The selected intervention model was the following ARIMA(2,1,0) with a drift:

$$\hat{y}_t - y_{t-1} = 0.488 - 0.661 y_{t-1} - 0.330 y_{t-2} - 2.988 TC_{1998} + 2.851 AO_{2000} + \varepsilon_t$$

The ARIMA model suggests that the linear trend observed in the FAOSTAT series will continue in the future, so that yields can reach around 65 tons per ha in 2050. On the other hand, yields in IMPACT grow slowly but level off after 2030 at around 48 tons per ha (Figure 3.6). Both forecasts are much lower than the 73 tons per ha projected by Jaggard et al. (2010) under a conservative growth scenario.

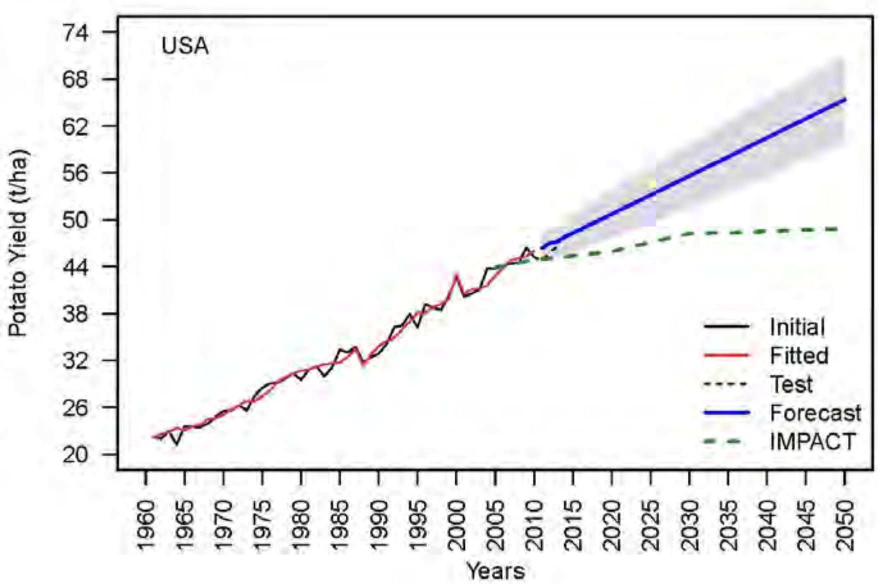


Figure 3.6. Potato yield forecast for the United States.

The question regarding the future of potato yields in – already – high yielding countries like the United States is not about closing a gap between actual and attainable yields but rather how to extend the current attainable yield ceiling. Douches et al. (1996) found that the yield growth recorded in the United States over the previous years was primarily the result of improvements in management, which suggests a smaller yield gap than other countries. On the contrary, most breeding programs targeted improvements in quality traits in order to meet the demands of the processing industry and the consumer. These findings imply that there may be room for genetic yield improvements, although the task of combining agronomic and quality traits in a single potato cultivar is certainly not trivial. The development of heat tolerant cultivars also seems to be a decisive factor which will allow the continuation of the current yield growth under climate change (Hijmans, 2003), but given the slow varietal change in the United States during the last decades (Walker et al., 2011a), the potential rate of adoption is uncertain and cannot be easily estimated. Nevertheless, recent studies forecast that the total factor productivity index[2] of the agricultural sector in the United States will continue to increase until 2050 (Wang et al., 2015) and this may be an important driver for further increases in potato yields in the future. From the previous discussion it is clear that the literature does not provide enough information towards the identification of a plausible "business as usual" scenario of future potato yield growth in the United States; both the ARIMA projections and the yields produced by IMPACT can represent such a scenario. Since the IMPACT yield projections lie outside the 95% ARIMA prediction interval, we propose adjustments to IPRs so that the model simulates an "average" scenario of yield growth which corresponds to final yield of around 57 tons per ha in 2050.

3.5. Germany, Netherlands and France

The discussion regarding future yields for the United States also applies for the case of European countries which are also achieving yields higher than 40 tons per ha. Germany, France and the Netherlands, together with Belgium and the United Kingdom are the largest potato producers in the European Union (EU) and the literature suggests that climate change will be an important determinant of future potato productivity in these countries. Such foresight evidence is provided by Hijmans (2003) who identified regions, especially in higher latitude, where the impact on potato yields is likely to be positive. A positive yield impact was also suggested by Ewert et al. (2005) who examined the role of technological development, climate change and increases in CO_2 concentrations on crop productivity in Europe. Finally, Leclère et al. (2013) argued that yields of tuber crops in Europe are likely to be positively affected if farmers follow appropriate adaptation strategies.

Climate change may also alter the spatial distribution of potato production, leading to a higher concentration in north-western European countries (Haverkort and Verhagen, 2008). This finding is affirmed by Hermans et al. (2010) who explored future European production of wheat, potato and milk under different climatic and socioeconomic scenarios but under the assumption of a

[2] Total factor productivity expresses the output growth which cannot be explained by the increased use of inputs. In this sense it is a measure of technical efficiency of input use and represents the impact of technological improvements on productivity.

complete liberalization of the EU. These authors also estimate that potato yields are likely to exceed 60 tons per ha in some regions of France, Germany and the Netherlands. Nevertheless, this spatial shift in potato cultivation will need to be accompanied by further yield growth so that the, already highly integrated and very competitive, European potato industry improves its positioning in the rapidly expanding global market of processed potato products and convenience-products. This, in turn, requires the development of new higher yielding varieties which will also offer better quality and higher resistance to biotic and abiotic factors (EC, 2007). Given the various successful examples of participatory breeding across many countries in the European Union (Almekinders et al., 2014), a further growth in productivity for potato cultivation is very likely to occur. In the following paragraphs we examine how IMPACT and estimated ARIMA models represent this growth scenario, but, as in the case of the United States, there is not enough information for a more accurate quantitative assessment of future yield levels. Hence, the proposed yield growth scenario will rely on the rule of thumb and the use of the ARIMA prediction intervals.

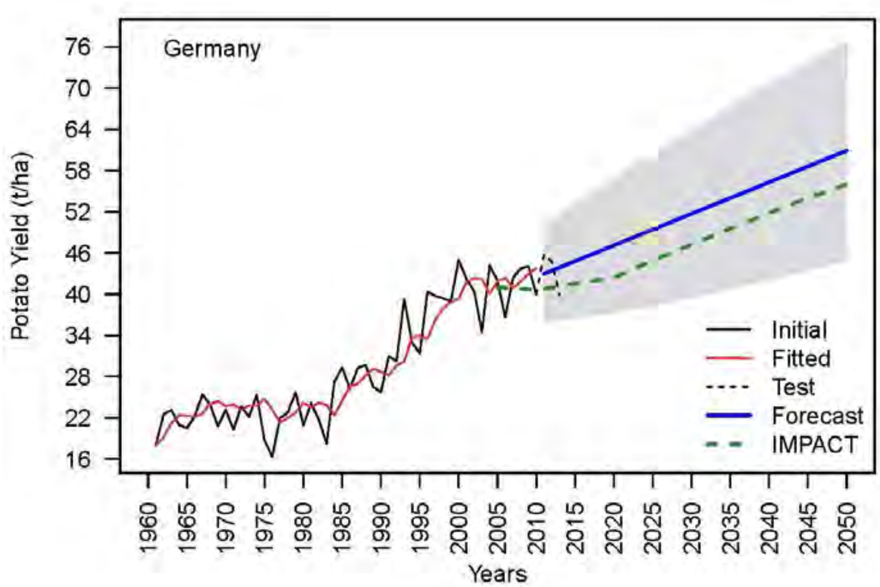


Figure 3.7. Potato yield forecast for Germany.

Beginning with Germany, no outliers were found in the yield series and the selected model was an ARIMA(0,1,1) with drift:

$$\hat{y}_t - y_{t-1} = 0.456 + \varepsilon_t - 0.665\varepsilon_{t-1}$$

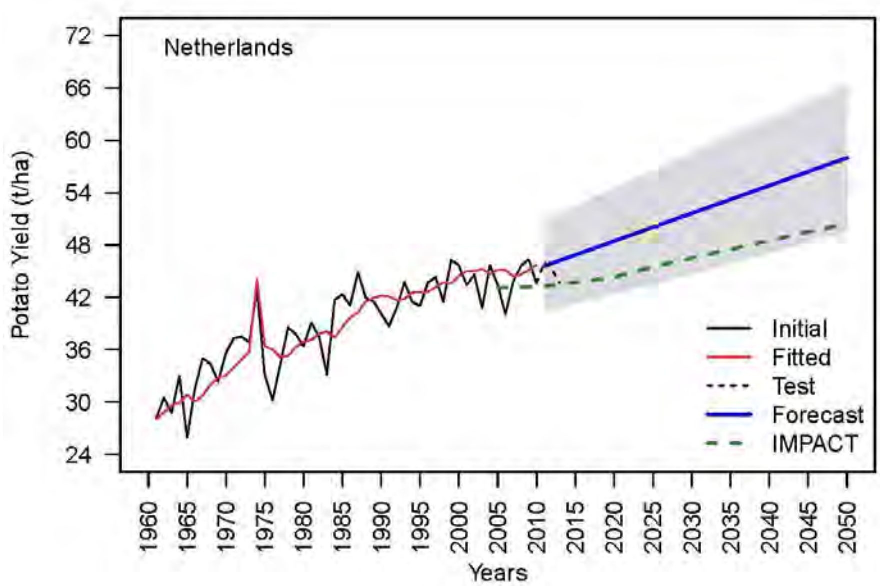
As can be seen from Figure 3.7, both IMPACT and the ARIMA model forecast almost the same yield growth rate but the ARIMA yields for 2050 are higher (56 vs. 61 tons per ha). Nevertheless, IMPACT projections lie inside the 95% prediction interval and therefore no IPR adjustments are proposed.

Regarding potato yields in the Netherlands, an additive outlier was detected in 1974 and the selected intervention model was an ARIMA(0,1,1) with drift:

$$\hat{y}_t - y_{t-1} = 0.318 + 7.760AO_{1974} + \varepsilon_t - 0.796\varepsilon_{t-1}$$

Both models suggest that yields will continue to increase in the future, but IMPACT produces a more moderate rate of growth with yields of around 50 tons per ha in 2050, contrary to the ARIMA forecast of around 58 tons per ha (Figure 3.8). However, since the former lies inside the 95% ARIMA prediction interval we consider it as a reasonable scenario of yield growth.

Figure 3.8. Potato yield forecast for the Netherlands.



Finally, the analysis of potato yields in France identified an additive outlier in 1976 and a temporary change in 1989. The additive outlier represents a fall in yields of about 12 tons per ha 18and is the result of the 1976 heat wave which affected several countries in Western Europe. Note that potato yields for Germany also exhibit a fall in 1976 but the effect on the ARIMA process is not statistically significant. The selected intervention model for France was an ARIMA(4,1,0) with drift:

$$\hat{y}_t - y_{t-1} = 0.572 - 0.922y_{t-1} - 0.785y_{t-2} - 0.652y_{t-3} - 0.472y_{t-4} - 11.916AO_{1976} - 4.973AO_{1989} + \varepsilon_t$$

IMPACT produces yields of around 49 tons per ha for 2050 which do not differ significantly with respect to 2010-2013 observations. On the contrary, the ARIMA model suggests a more rapid productivity growth with yields of around 67 tons per ha in 2050 (Figure 3.9). Since the IMPACT yield projections lie outside the 95% ARIMA prediction interval, we propose adjustments to IPRs so that the model simulates an "average" growth scenario which leads to yields of around 58 tons per ha in 2050.

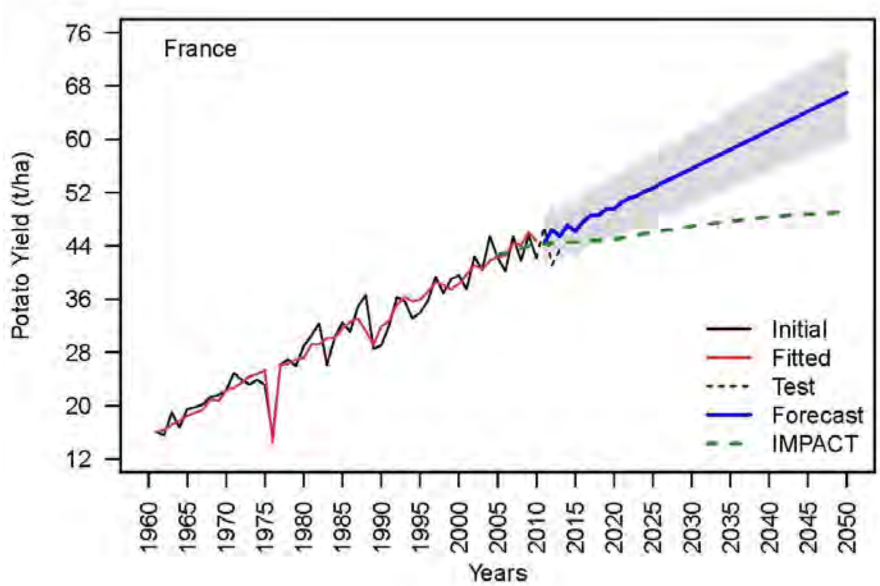


Figure 3.9. Potato yield forecast for France.

3.6. Bangladesh

Potato is the principal vegetable in Bangladesh and the second most important crop behind rice. Its cultivation is widely distributed across the country where it is grown mainly as a cash crop and regarded as a high value commodity (CIP, 2006). Like in other Asian countries, potato production in Bangladesh has greatly expanded during the last decades, especially after 2000 when output surged from about 1.5 million tons to more than 8 million tons in 2013 (FAO, 2015). This impressive growth, besides the rising domestic demand as a result of the "westernization" of dietary preferences in urban areas (Pingali, 2006), can also be attributed to the introduction of several improved high yielding varieties and the development of cold storage facilities which increased the temporal availability of potato, while producers also gained significant price advantages (Reardon et al., 2012). Potato yields in Bangladesh have followed a similar growth pattern and have been increasing constantly, albeit moderately since 2000. The analysis of the yield series revealed an additive outlier in 2009 and the intervention model which gave the lowest AICC score was the ARIMA (0,1,0) – a random walk – with a drift:

$$\hat{y}_t - y_{t-1} = 0.247 - 4.045AO_{1989} + \varepsilon_t$$

Although the slope of the linear trend forecast by the ARIMA model is comparable to that of the IMPACT forecasts, the absolute yield level differs and IMPACT is not able to approximate the reported yields for 2010-2013 adequately (Figure 3.10). Furthermore, the yield trend in IMPACT shows signs of leveling off after 2025 so that yields in 2050 does not exceed 22 tons per ha, whereas the ARIMA model forecasts yields of around 28 tons per ha in 2050. The ARIMA projection seems a more plausible scenario of future yield growth because potato is grown in Bangladesh as a cash crop, usually in rotation with rice and with adequate soil water (Scott and Suarez, 2012c), and has exhibited steadily increasing indices of total factor productivity during the last 30 years (Baset et al., 2009). Indeed, some regions in the country are already achieving average yields of more than 24 tons per ha, while maximum yields in excess than 36 tons per ha have also been reported (Azimuddin et al., 2009). Furthermore, recent research suggests that a more efficient use of inputs could reduce the existing yield gap and lead to higher actual yield levels (Baset et al., 2009; Monayem Miah et al., 2013), while agronomic trials have demonstrated the ability of several existing varieties to achieve attainable yields in excess of 40 tons per ha under irrigated conditions (Amanullah et al., 2010).

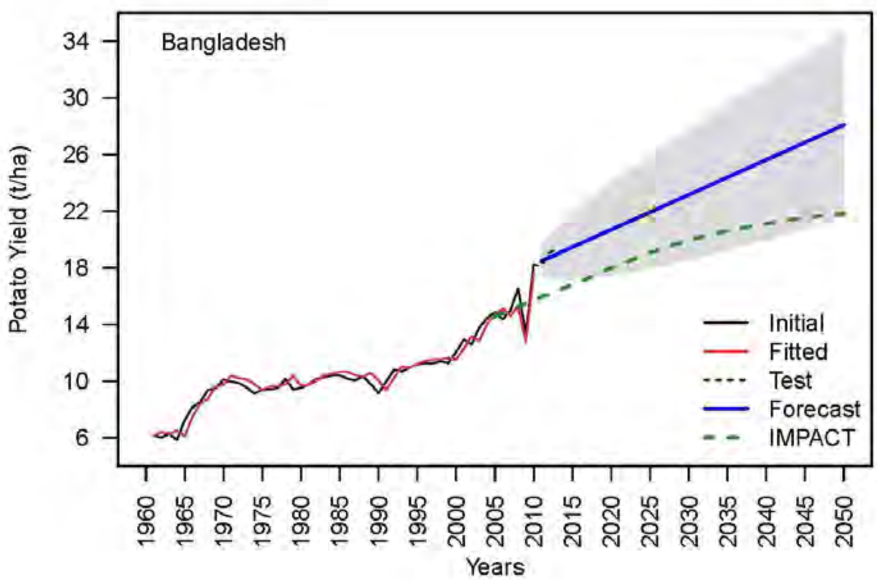


Figure 3.10. Potato yield forecast for Bangladesh.

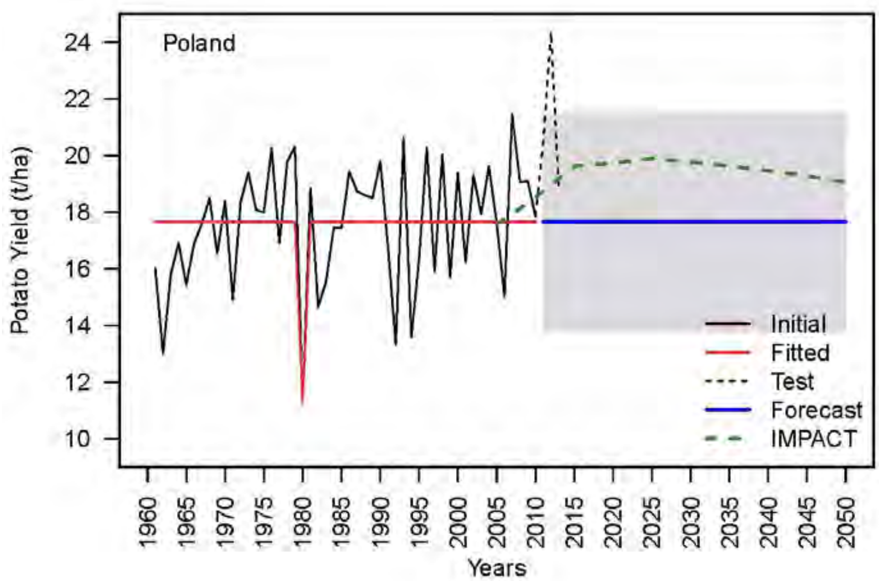
3.7. Poland

Poland has traditionally been one of the largest potato producers in the European continent but total output has been steadily declining since the 80's and is currently below 8 million tons. This evolution of production has been the result of changes in consumer preferences and the reduced use of potato as animal feed which is being replaced mostly by grain crops. At the same time, potato in Poland is still a subsistence crop in many regions and it is grown by small holder farms with little market orientation (EC, 2007). The fall in output over the last years has been driven by a steep decrease in cultivated land, from almost 3 million hectares in 1961 to less than 500,000 in 2013 (FAO, 2015). On the contrary, potato yields in Poland seem to follow a level trend and are highly volatile due to a sequence of extreme climatic events like excessive precipitation in one year followed by drought the next year (IUNG, 2015). Despite the high volatility, the series is stationary, as indicated by the KPSS test. Further testing with the ADF also rejected the hypothesis of a unit root. Additionally, the series appears to be almost white noise since the correlogram for lag 50 revealed a single significant autocorrelation at lag 13, while no partial autocorrelations where found up to the same lag order. These results indicate that the process describing the evolution of potato yields in Poland should not contain any AR or MA components. Indeed, the model which passed all diagnostic checks, including that of normality, was an ARMA(0,0) intervention model with a non-zero mean, i.e., purely white noise around a constant. The model also includes a single pulse (dummy variable) which accounts for an additive outlier detected in 1980. The intervention model can be mathematically expressed as:

$$\hat{y}_t = 17.657 - 6.397 AO_{1980} + \varepsilon_t$$

Figure 3.11 presents the forecast from the estimated model. It is obvious that a white noise process corresponds to a simple linear regression model where the pulse intervention is the only exogenous variable. As a result, the forecast is a straight line and consequently the model fails to capture the yield increase observed in the test period.

Figure 3.11. Potato yield forecast for Poland using 1961-2010 data.



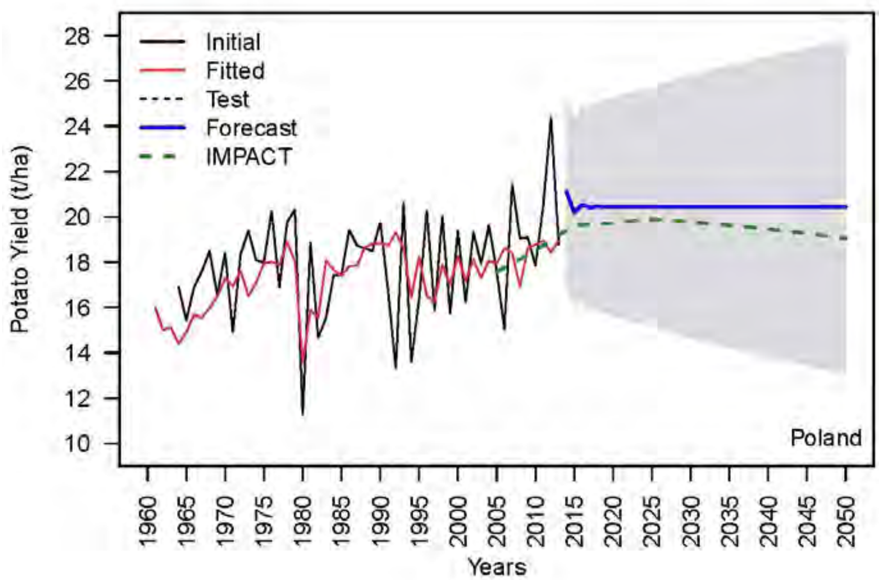
Note that when examining all 53 observations the yield growth observed in 2010-2013 does not seem to be an outlier. Furthermore, when considering the entire sample, the KPSS test indicates that the series is $I(1)$ stationary which shows that the stochastic process has changed after 2010; the model with the lowest AICC value is now an ARIMA(1,1,1) and the outlier in 1980 is interpreted as a temporary change:

$$\hat{y}_t - y_{t-1} = -0.397 y_{t-1} - 5.038 TC_{1980} + \varepsilon_t - 0.654 \varepsilon_{t-1}$$

The forecast of the ARIMA(1,1,1) model is also a level yield and therefore the in-sample forecast accuracy is still low. Interestingly, and as shown in Figure 3.12, the almost linear trend of future yields produced by IMPACT is very close to the forecast from the ARIMA(1,1,1) model. However, the yield surge in 2012 and latest information on the 2014/2015 harvest when national average potato yields reached 27.9 tons per ha (Euro-Potato, 2014) provides evidence of an increasing trend which is not captured either by IMPACT or the ARIMA forecasts. This trend can be attributed to the fact that while potato cultivated area is declining, land dedicated to seed production has not changed and this leads to a higher proportion of potato being produced by healthy seed (Wróbel and Wąsik, 2014). However, there is still room for improving seed quality, and consequently farm yields, since Poland is using lower seed certification standards than many western European countries and the European Union is planning a uniform classification scheme for seed potatoes which will impose higher quality requirements (ESA, 2010). At the same time, although an important part of potato consumption in Poland is still not commercialized, modern processing industries have already been established and the production of french fries and chips shows an increasing trend which is expected to continue in the following years, driven mainly by the growing foreign demand for such products (Kobuszynska, 2012).

From the above discussion we conclude that there are prospects for productivity growth in the future and national average yields of 30 tons per ha can be seen as a reasonable growth scenario. Therefore, the post-2014 IPRs should be adjusted upwards to reflect this increasing trend.

Figure 3.12. Potato yield forecast for Poland using 1961-2013 data.



4. SWEETPOTATO YIELD FORECASTS FOR 2050

Figure 4.1 presents the evolution of sweetpotato yields in the ten largest producing countries of the world.

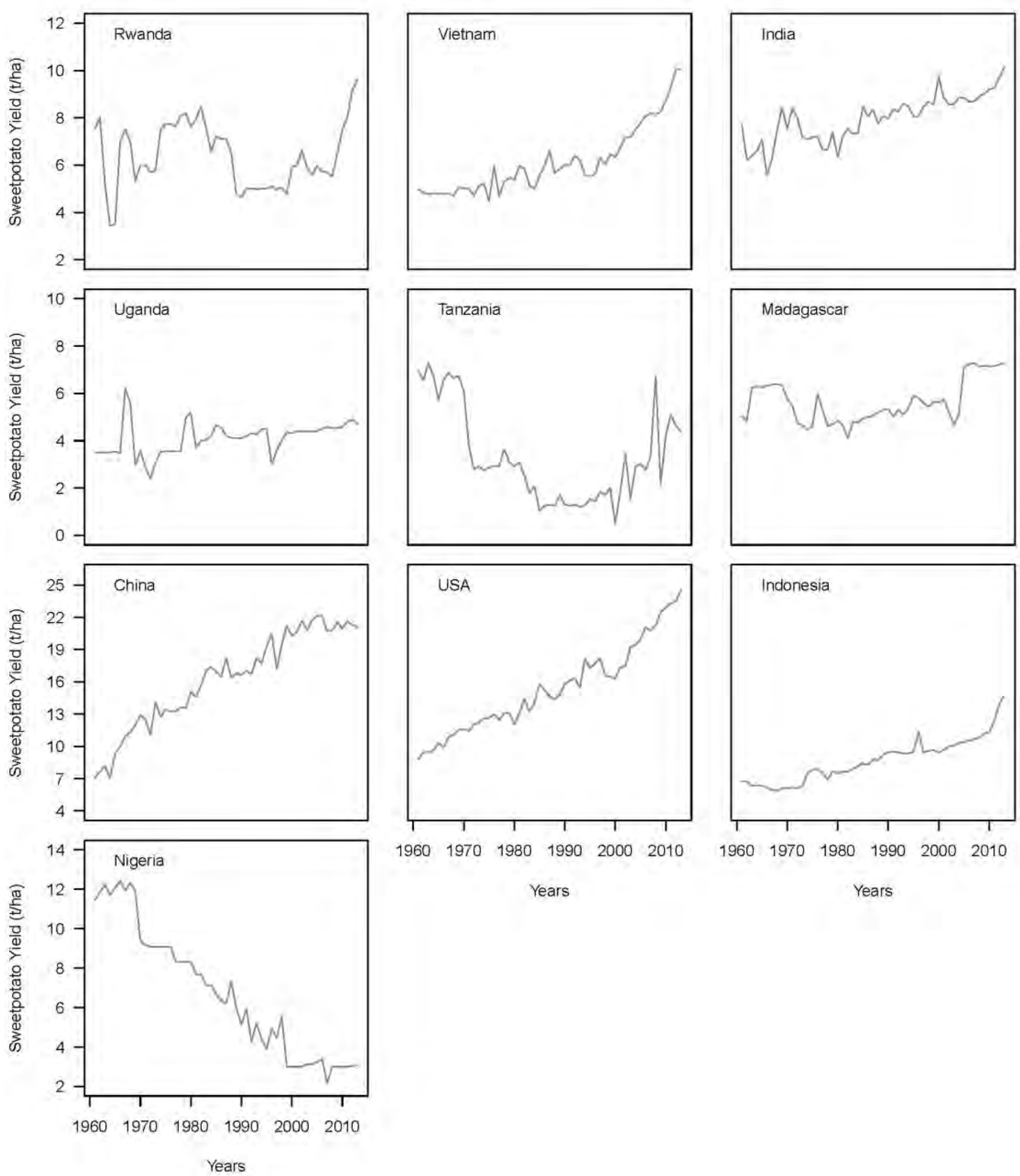


Figure 4.1. Sweetpotato yields in the world's largest producing countries.

One interesting observation is that yields for the five African countries in 2013 are below the world average of 12.6 tons per ha (FAO, 2015) and they are either decreasing (Nigeria) or seem to be fluctuating around a level yield. A second observation is that, contrary to potato, the yield difference between developed and developing countries is not as pronounced, as can be clearly be seen by comparing yields achieved in 2013 in China and the United States (21.1 and 24.5 tons per ha respectively). In fact, three African countries, Ethiopia, Egypt and Mali are among the countries with the highest yields recorded in 2013, with 34.7, 32.3 and 25.5 tons per ha respectively (FAO, 2015). However, given the low quality of national average data, these numbers should be viewed with caution.

Although there are numerous studies examining the factors that constrain sweetpotato productivity in different regions in the world, there is a big gap in the literature regarding the modeling of sweetpotato farming systems and the future prospects of sweetpotato cultivation. Characteristic of this gap is that only two sweetpotato crop models have been identified in the literature, and neither has been used, or is ready to be used for climate change studies (Raymundo et al., 2014). As a result, the impact of climate change on sweetpotato yields has not been studied adequately. A similar gap also exists for the economic analysis of sweetpotato cultivation, since, to the extent of our knowledge, there exists no study on foresight modeling of sweetpotato production, probably due to its secondary role in farming systems in most developing countries. The low quality of national data in the FAOSTAT database, especially for SSA (Walker et al., 2011b), is another problem which relates more to the statistical analysis of time series data, as in this report. Despite these problems, in the following paragraphs we attempt a rapid but comprehensive review of the existing literature on sweetpotato productivity in the ten biggest producing countries in the world in order to evaluate the yield growth trajectories produced by IMPACT and the ARIMA model.

4.1. China

Sweetpotato seems to have first appeared in China sometime during the 16th century and was most probably brought in by overseas merchants (O'Brien, 1972). Since that time, sweetpotato cultivation in the country has greatly expanded and now China is the largest producer in the world with annual average yields that exceed 20 tons per ha. Yields in China have increased during the second part of the last century, but they seem to have stagnated after 2000. In contrast, total sweetpotato output in the country has contracted, driven by a decline in harvested areas.

The sweetpotato yield series in China does not contain any outliers. Since the series is growing, it is obviously not stationary. First order differencing was sufficient for obtaining a stationary series and the selected model was an ARIMA(2,1,0) with drift:

$$\hat{y}_t - y_{t-1} = 0.286 - 0.583 y_{t-1} - 0.334 y_{t-2} + \varepsilon_t$$

As in the case of potato, IMPACT does not approximate adequately reported sweetpotato yields for the 2010-2013 period and therefore the respective IPRs should be adjusted downwards. Regarding the long term forecasts of the two models, IMPACT produces a concave trend leading to 27 tons per ha in 2050, whereas the ARIMA forecasts a linear growth resulting in approximately 33 tons per ha for the same year (Figure 4.2).

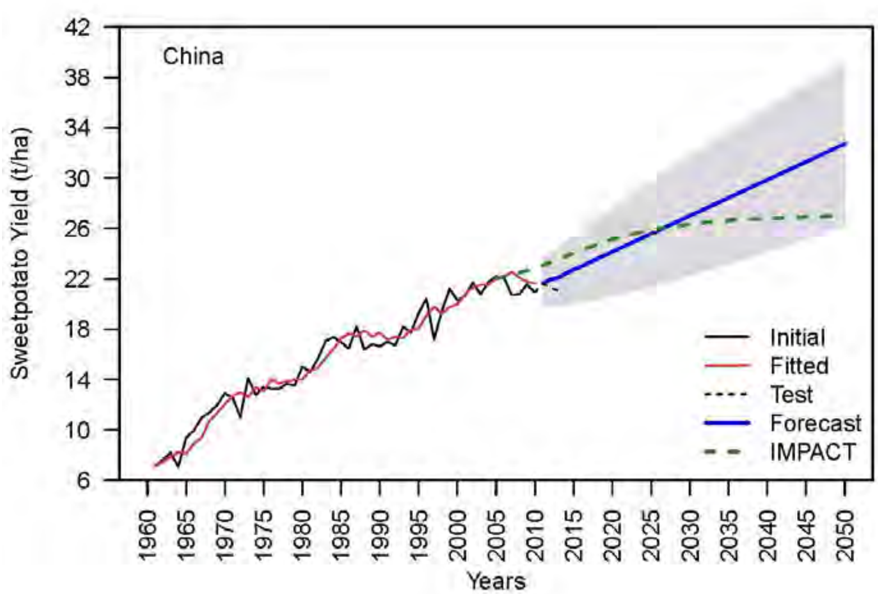


Figure 4.2. Sweetpotato yield forecast for China.

Sweetpotato in China is concentrated mainly in the Yellow River and the Yangtze River valleys. These regions exhibit high yield variability and Zhang et al. (2009) presents data from the 2005 China Year Book of Agriculture which shows that actual yields of over 35 tons per ha have already been reported regionally. Achieving such average yields at the national level, as per the ARIMA forecasts, requires further development and adoption of higher-yielding, and more pest- and virus-resistant varieties. Given the successful sweetpotato breeding program in China which was aided by the introduction of germplasm from other countries and institutions (CIP, 1999), average national yields higher than 30 tons per ha by 2050 are not unlikely. There are also economic incentives which may promote this yield growth. More precisely, sweetpotato in China has been traditionally used for human consumption but the increase in consumers' income and the consequent changes in dietary preferences that were brought about by the economic reforms in the 80's have modified its usage patterns. As a result, sweetpotato utilization nowadays is mainly directed towards higher value uses; about 45% of total sweetpotato root production is used as feed, primarily for pigs (Peters, 2004), while a smaller part is also utilized in food industries, some of which are export-orientated (Zhang et al., 2009). At the same time sweetpotato in China is used for the production of ethanol fuel, albeit to a small scale. However, recent studies have shown that non-grain crops, such as sweetpotato, will form the basis of the bio-ethanol industry in China and are likely to drive their price upwards (Qiu et al., 2010), thus providing further incentives to increase productivity. From the previous discussion we conclude that the ARIMA forecasts of 33 tons per ha in 2050 are a realistic and plausible scenario of yield growth. Therefore, we propose the adjustment of the IPRs to better simulate this trend.

4.2. United States

Although the production and consumption patterns of sweetpotato in the United States have varied during the 20th century, sweetpotato has always been a vegetable primarily consumed fresh at home. Through breeding, improvement of management practices, high quality planting materials, irrigation and efficient use of chemical fertilizers, together with the development and commercialization of the sweetpotato industry (Smith et al., 2009), yields in the United States have almost tripled since 1960 and the country now accounts for almost 1% of global production.

The analysis of the sweetpotato yield series in the United States revealed a temporary change in 1994 and a level shift in 2003. A possible reason for the structural break is that 2003 represents the first growing season after the finalization of the standards for organic farming in the United States which may have prompted sweetpotato farmers to increase productivity as a result of premium price expectations for their products (Greene and Kremen, 2003). The selected intervention model was the following ARIMA(0,1,1) with drift:

$$\hat{y}_t - y_{t-1} = 0.238 + 2.043TC_{1994} + 1.859LS_{2003} + \varepsilon_t - 0.516\varepsilon_{t-1}$$

Sweetpotato yields have increased almost linearly in the United States since 1960 (Figure 4.3), and the ARIMA model forecasts the continuation of this linear trend into the future with a final projected yield of 32 tons per ha in 2050. On the contrary, IMPACT produces an exponential yield growth which results in 47 tons per ha in 2050.

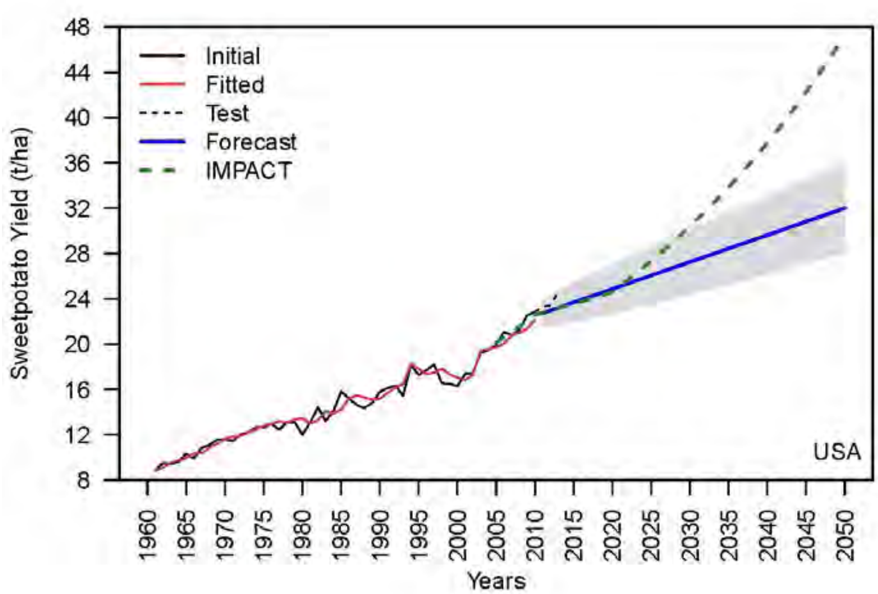


Figure 4.3. Sweetpotato yield forecast for the United States.

Although sweetpotato yields in the country are already high, there also exists a large variability among the principal producing States; California has achieved the highest average yields in 2014 with more than 33 tons per ha, while the lowest have been reported in Mississippi where yields did not exceed 21 tons per ha (Johnson et al., 2015). Smith et al. (2009) attribute this big yield difference to the milder agro-ecological conditions of the west coast, especially with regards to weather extremes and biotic pressures. Furthermore, sweetpotato fields in California are mostly irrigated, whereas in the eastern States sweetpotato is typically grown as a rainfed crop and it is subject to water availability problems, which results in a higher yield gap between attainable and actual yields. Therefore, in order to increase productivity, breeding for higher yielding and pest- and drought-resistant varieties is required, together with economic incentives brought about by increased sweetpotato demand. As regards to the latter, the changing dietary preferences towards spicier foods and alternative vegetables have not favored domestic sweetpotato demand. However, continuous efforts by the industry to promote the nutritional and health benefits of the crop have stabilized this trend, leading to a slight increase in sweetpotato consumption per capita during the last decade (Estes, 2009). By also taking into account the increasing domestic and foreign demand for processed sweetpotato products, the future for sweetpotato cultivation in the United States seems promising (Johnson et al., 2015). From the previous discussion we conclude that yield growth in the United States, expressed by the continuation of the historically observed linear trend, is indeed a plausible scenario. In this sense the exponential growth projected by IMPACT seems to be highly optimistic, especially given the lack of studies on the likely impacts of climate change on sweetpotato yields. Since the IMPACT yield projections lie outside the 95% ARIMA prediction interval, we propose adjustments to post-2020 IPRs to better simulate a linear growth pattern which corresponds to an "average" scenario of yield growth and leads to yield of around 39-40 tons per ha in 2050.

4.3. India

Sweetpotato is cultivated as a rainfed crop in India and it is mainly consumed as a fresh vegetable, having very weak ties with the industry. Because of its secondary role in local diets and the lack diversified sweet potato products that can provide income-generation opportunities for the farmer, output in India has contracted in recent years, driven by a decline in cultivated areas (Srinivas, 2009). On the contrary, sweetpotato yields have exhibited moderate growth, with a level shift detected in 1968, and are currently above 10 tons per ha. The intervention model selected was an ARIMA (0,1,1):

$$\hat{y}_t - y_{t-1} = 1.516LS_{1968} + 1.859LS_{2003} + \varepsilon_t - 0.563\varepsilon_{t-1}$$

The ARIMA model forecasts a constant yield of around 9 tons per ha until 2050 while IMPACT projects increasing yields (a concave trend) that reach 14 tons per ha in 2050 (Figure 4.4)

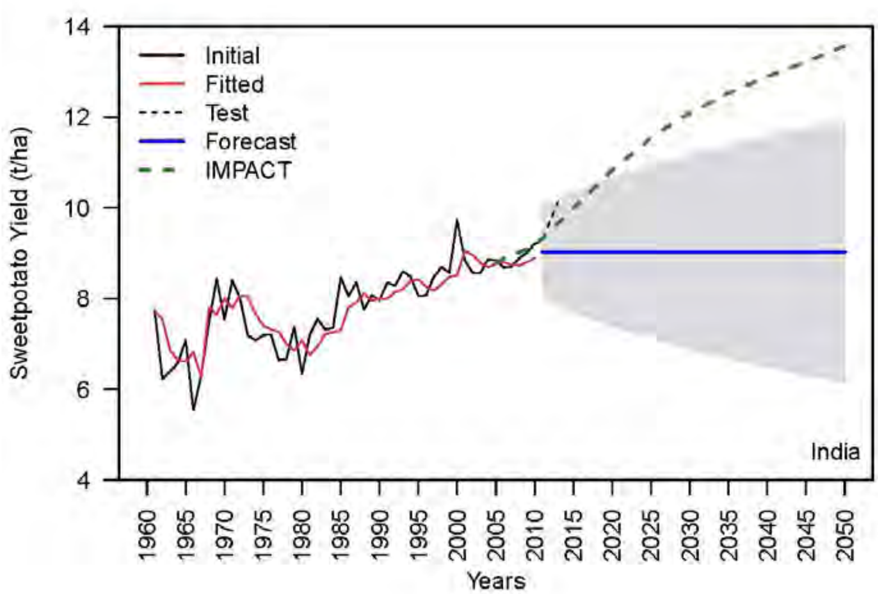


Figure 4.4. Sweetpotato yield forecast for India.

Sweetpotato is an under-exploited crop in India and the prospects for yield growth will depend on the efforts to promote the crop's nutritional benefits, especially of OSFP varieties, as a means to prevent vitamin A deficiency and to improve the livelihoods of the producing households. CIP plays an important role in aiding national plans to achieve this goal by actively promoting the cultivation of OSFP in the Orissa region through participatory trials of new OFSP varieties and the training of farmers (Attaluri et al., 2010). Orissa is India's primary sweetpotato producing state which accounts for almost one third of total sweetpotato in the country but with below-average yields. Although recent data show evidence of yield growth, which suggests possible adoption of improved production technologies (Sivakumar et al., 2008), sweetpotato in Orissa is still grown as a supplement to rice with minimum inputs and exchanged for other products in a barter economy system (Edison et al., 2009). However, given the success of CIP's promotional program to increase awareness of the crop's nutritional benefits and to improve production practices, it is expected that OFSP cultivation will expand and productivity will increase in the future. This may also trigger improvements in the marketing chain and create stronger ties with the food processing industry, thus leading to more diversified and value-added products. This future scenario is well described by the increasing yields produced by IMPACT.

4.4. South-East Asia

The South-East Asian countries that we focus on are Vietnam and Indonesia which account for more than 80% of total sweetpotato output in the region (FAO, 2015). Sweetpotato production in Vietnam is mostly concentrated in the Red River Delta in the central and northern parts of the country where it is grown for food and animal feed purposes in small-scale farming as part of rice-rotation systems. In the Mekong River Delta of the south, sweetpotato is less common and it is grown both as a food and a cash crop (CIP, 2006). Production in Vietnam has increased significantly after the war, and even surpassed 2.5 million tons in 1981 and 1992. However, this last surge was followed by a decreasing trend and nowadays annual production has fallen below 1.5 million tons (FAOSTAT, 2015). This decline in output is mainly caused by the shift of local farming systems towards more high-value crops such as vegetables (Campilan, 2009) and is expressed through a reduction in cultivated land. At the same time, sweetpotato yields in the country have grown significantly since the mid-nineties and in 2013 they exceeded 10 tons per ha. The analysis for the sweetpotato yield series in Vietnam revealed two temporary changes in 1983 and 1994, and two additive outliers in 1976 and 1987. The selected intervention model for the sweetpotato yield series in Vietnam is an ARIMA(1,1,0) with drift:

$$\hat{y}_t - y_{t-1} = 0.075 - 0.425 y_{t-1} + 0.995 AO_{1976} - 0.918 TC_{1983} + 0.848 AO_{1987} - 0.896 TC_{1994} + \varepsilon_t$$

IMPACT approximates adequately the rapid yield growth reported during the last decade growth. Both the ARIMA model and IMPACT suggest that this growth will continue in the future, although IMPACT produces a concave trajectory which results in 13 tons per ha in 2050, whereas the final ARIMA yield forecast is lower (11.6 tons per ha). Since no information could be inferred from the literature regarding future sweetpotato yields in Vietnam, we rely on the rule of thumb to draw a likely scenario of productivity growth. Thus, since the IMPACT yield projections lie inside the ARIMA prediction interval (Figure 4.5), we do not propose any IPR adjustments.

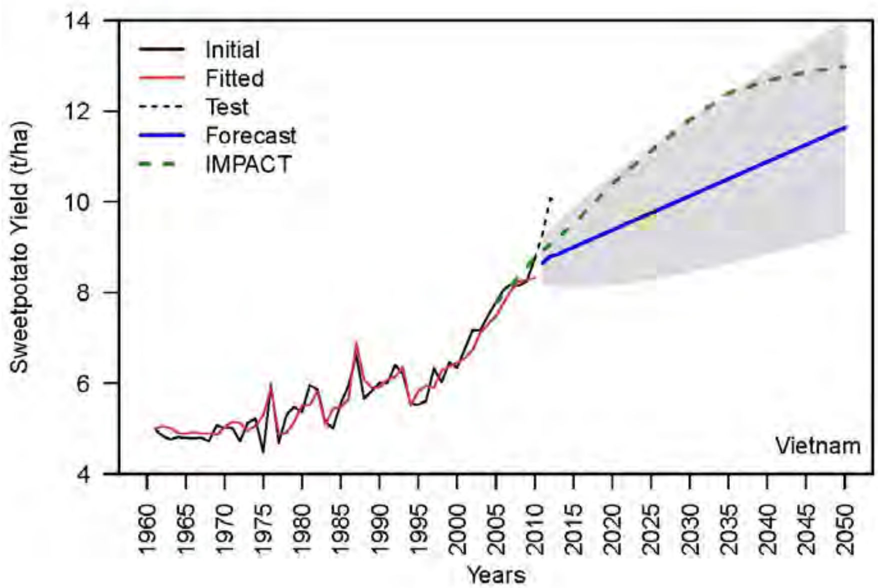


Figure 4.5. Sweetpotato yield forecast for Vietnam.

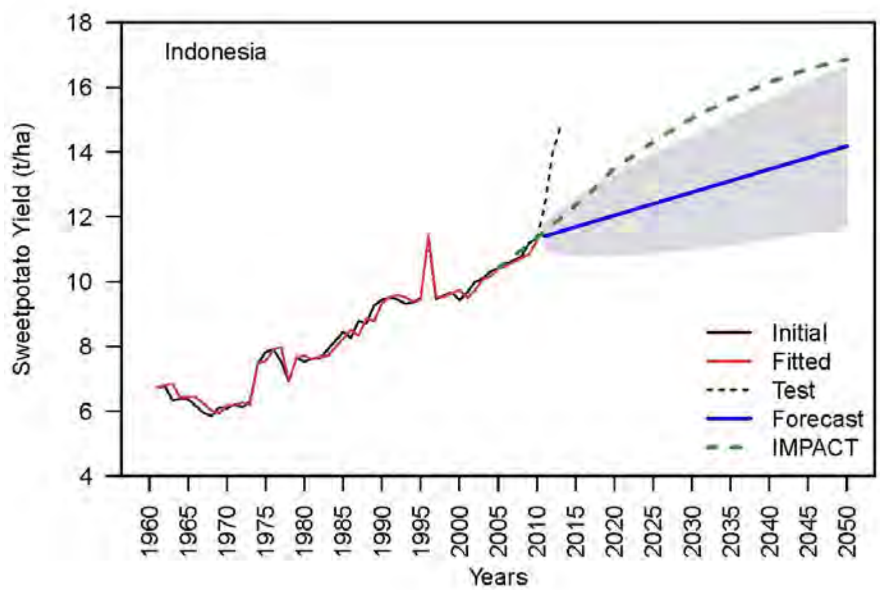
In Indonesia, the use of sweetpotato varies from a cash crop in the eastern rainfed part of the country, to an important staple and pigfeed in Java and West Papua (Campilan, 2009). Contrary to the rapid increase in Vietnam during the 80's, sweetpotato output in Indonesia has remained relatively stable during the last four decades, oscillating around a production level of 2 million tons. Yields, however, have increased significantly since 1961 and are now above 14 tons per ha. The statistical analysis of the yield series revealed a level shift in 1974 and two additive outliers in 1978 and 1996 and the model which best described the evolution of the yield series was the following ARIMA(0,1,0) with a drift:

$$\hat{y}_t - y_{t-1} = 0.071 + 1.109LS_{1978} - 0.665AO_{1978} + 1.880AO_{1996} + \varepsilon_t$$

IMPACT approximates the yields for 2005-2009 very well but it produces poor forecasts for 2010-2013. However, given the evolution of the series until 2010, the question that arises is whether the values that are observed in 2011-2013 are outliers or a normal evolution of the stochastic yield growth process (Figure 4.6). Indeed, the outlier hypothesis is confirmed when the entire

1961-2013 sample is used. In this case, the iterative procedure suggests that yields in 2011 and 2012 constitute level shifts whereas 2013 is an additive outlier.

Figure 4.6.
Sweetpotato yield forecast for Indonesia.



Although the statistical analysis suggests that yields for 2011-2013 do not follow a pattern consistent with the remaining series, we have not succeeded in identifying any reason that could explain this rapid yield growth. In fact, all literature sources suggest that the crop is currently under exploited in Indonesia and there is a huge potential for the further expansion of sweetpotato production due to a large existing yield gap. For example, surveys from sweetpotato growing districts at the island of Java revealed that very few farmers applied any type of pesticide to control damages from insects, while at the same time they were not able to recognize the symptoms of viral disease in their crops (Nasir et al., 2003). The surveys also showed that, although recorded yields in certain cases exceeded 25 tons per ha, an important reason of the overall low productivity in the region was the low quality of the vine cuttings as planting materials. Training of farmers and the use of improved management practices can increase yields and reduce production costs (Van de Fliert et al., 2001), but the cost of transportation, which is one of the main constraints in the development of the sweetpotato processing industry, probably requires a national strategy approach. Note that there is no accurate information regarding the proportion of sweetpotato production used in processing, but it is known that sweetpotato is used in some food industries as a thickener for sauces. The adoption of more efficient farming methods will also help to realize the potential of high-yielding varieties that have reportedly achieved yields of almost 40 tons per ha in field trials (Jusuf, 2003).

From the previous discussion it is obvious that the literature does not provide enough information for characterizing a plausible future scenario for sweetpotato yields in Indonesia. However, the statistical analysis of the series suggests that sweetpotato productivity will continue exhibiting moderate growth which will result in yields of 14 tons per ha in 2050. On the contrary, IMPACT forecasts a yield of 17 tons per ha for the same year but this projection lies outside the ARIMA prediction interval (Figure 4.6). For this reason, we propose adjustments to IPRs so that the model produces an "average" final yield of around 15-16 tons per ha in 2050.

4.5. Sub-Saharan Africa

The Sub-Saharan African countries that we focus on are Nigeria, Uganda, Madagascar, Tanzania and Rwanda (as in Table 1.2). Although yields in these countries are among the lowest in the developing world, production of sweetpotato has grown significantly during the last decade with the most impressive increase in output recorded in Tanzania; from almost 500,000 tons in 2000 to 3.5 million tons in 2013 (FAOSTAT, 2015). Sweetpotato in SSA is grown mainly by small holder farms with limited inputs under rainfed conditions, usually as a supplement to other food crops such as maize and cassava, with the latter being the dominant root and tuber crop in the region (Andrade et al., 2009). According to Low et al. (2009), this rapid growth of sweetpotato production in SSA can be attributed mainly to (i) changes in cropping patterns due to decline in government support of grain crops and (ii) the development of, mostly local yet still small, markets which help the transformation of sweetpotato from an important staple to a cash crop. This increase in output has been driven by an expansion in cultivated land while yields have stagnated, oscillating around different levels in each country. Instances of extreme temporary yield growth are apparent in the FAOSTAT time series, but Walker et al. (2011b) stress the "guesstimate" nature of the data, and question the reliability of the series, especially their high volatility; sweetpotato production statistics are difficult to estimate in SSA since the crop is usually grown and consumed locally by independent smallholders on small plots (CIP, 2006). This leads to highly unreliable national average data that complicate the modeling of sweetpotato yield time series and the evaluation of any type yield forecasting result. Finally, because of the (i) in-house consumption of the crop in SSA, (ii) the lack of sweetpotato processing industries and established markets, and (iii) the shift of consumers' preferences towards grain and meat products as a result of income increases in urban areas, information on the prospects of sweetpotato yield growth is limited.

We begin the time series analysis with Nigeria, whose yields have exhibited a decreasing trend since the beginning of the 70's and are presently leveled at about 3 tons per ha. The outlier analysis revealed two level shifts in in 1970 and 1999 and an additive outlier in 1988. The intervention model with the lowest AICC score was the following ARIMA (1,1,0):

$$\hat{y}_t - y_{t-1} = -0.551 y_{t-1} - 2.756 LS_{1970} + 1.490 AO_{1988} - 2.086 LS_{1999} + \varepsilon_t$$

Although the above model is acceptable by all diagnostic tests, the model which actually produced the lowest AICC value was an ARIMA(1,1,0) with a drift. However, because of the downward trend of the series, the drift term was negative and led to negative yield projections. For this reason, we omitted the constant from the outlier detection and model estimation process.

The selected ARIMA model leads to constant future yields of 3 tons per ha that imply very accurate in-sample forecasts. On the contrary, IMPACT produces an almost exponential growth trend and therefore fails to capture reported yields for 2005-2013. This suggests that the respective IPRs should be adjusted downwards. The exponential growth finally leads to yields of almost 11 tons per ha in 2050 (Figure 4.7) but this projection lies outside the ARIMA prediction interval. For this reason, and according to our rule of thumb we propose "average" final yield of 6-7 tons per ha in 2050.

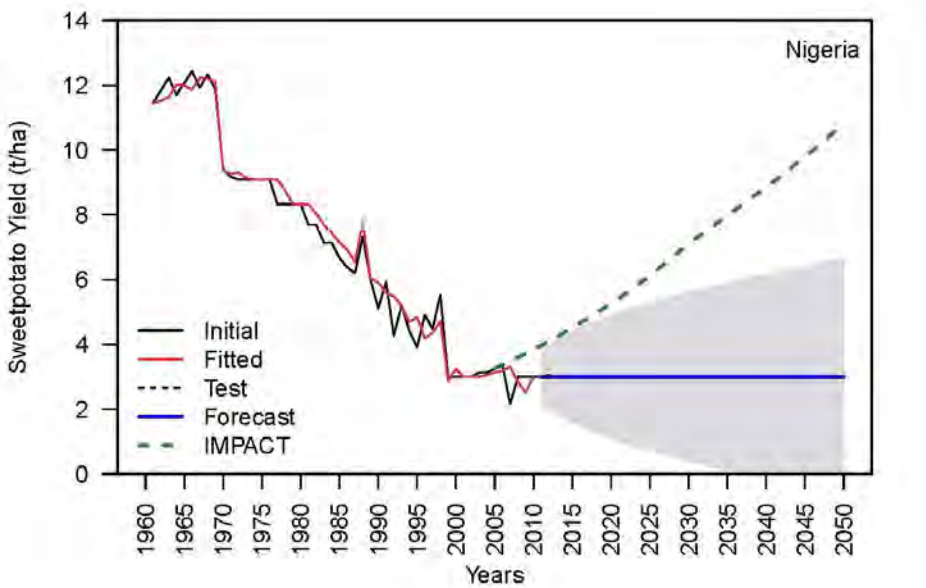


Figure 4.7.
Sweetpotato yield forecast for Nigeria.

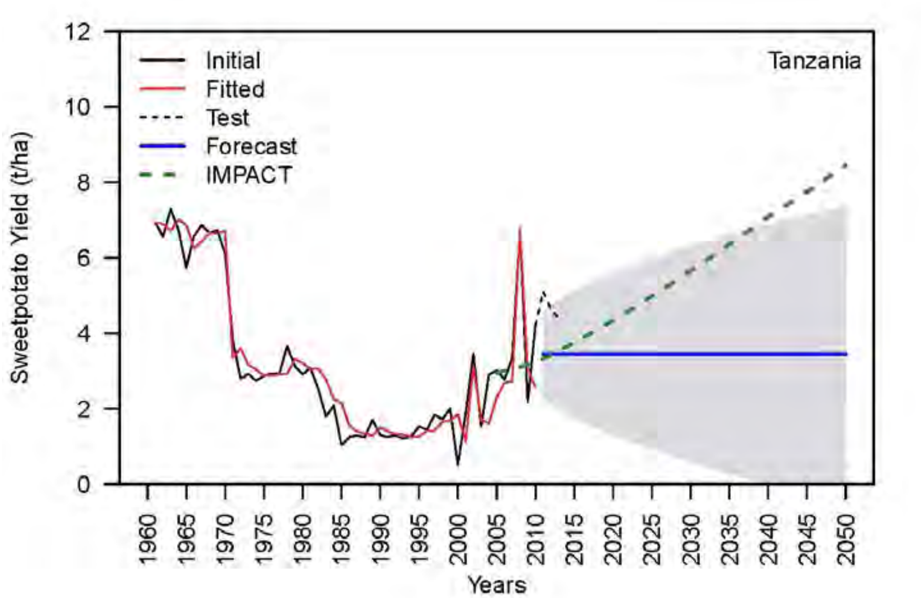
The outlier analysis for the sweetpotato yield series in Tanzania revealed a level shift in 1971 and two additive outliers in 2002 and 2008. The selected intervention model was an ARIMA(0,1,1):

$$\hat{y}_t - y_{t-1} = -3.027LS_{1971} + 1.606AO_{2002} + 3.735AO_{2008} + \varepsilon_t - 0.465\varepsilon_{t-1}$$

Similarly, to Nigeria, IMPACT does not produce a good approximation of the reported FAOSTAT yields, returning high MAPE scores for both sub-periods (2005-2009 and 2010-2013). However, the MASE for 2005-2009 is very small (0.29), which means that the low accuracy of the model in this period is the result of the high volatility of the series.

Regarding out-of-sample forecasts, post-2014 yields in IMPACT increase almost linearly and reach 8.5 tons per ha in 2050, whereas the ARIMA model produces a level yield trend of 3.5 tons per ha (Figure 4.8). Since the IMPACT yield projections are outside the ARIMA prediction interval, we propose IPR adjustments that correspond to an "average" yield scenario of 6 tons per ha in 2050.

Figure 4.8. Sweetpotato yield forecast for Tanzania.



Two temporary changes in 1967 and 1969 and a level shift in 1979 are detected in the case of Uganda. The intervention model that returned the lowest AICC value was the ARMA(0,1) with a constant, in other words, a moving average (MA) process:

$$\hat{y}_t = 3.508 + 2.771TC_{1967} - 2.130TC_{1969} + 0.800LS_{1979} + \varepsilon_t$$

Contrary to other yield series, the Jarque-Berra test rejected the hypothesis of a residual normal distribution. However, since the residuals of every model tested up to a and lag order of 5 also did not provide evidence of a normal distribution, and given the discussion in the methodology section on whether crop yields are actually normally distributed, we decided to keep the above estimated model.

The selected MA model shows that the Uganda sweetpotato yield series is stationary and forecasts a level yield trend of about 4 tons per ha until 2050 (Figure 4.9). On the contrary, sweetpotato yields in IMPACT exhibit an almost linear growth and finally exceed 10 tons per ha in 2050 which, however, lies outside the ARIMA prediction interval. According to our rule of thumb, yields of 7.5 tons per ha in 2050 represent an acceptable "average" scenario of productivity growth.

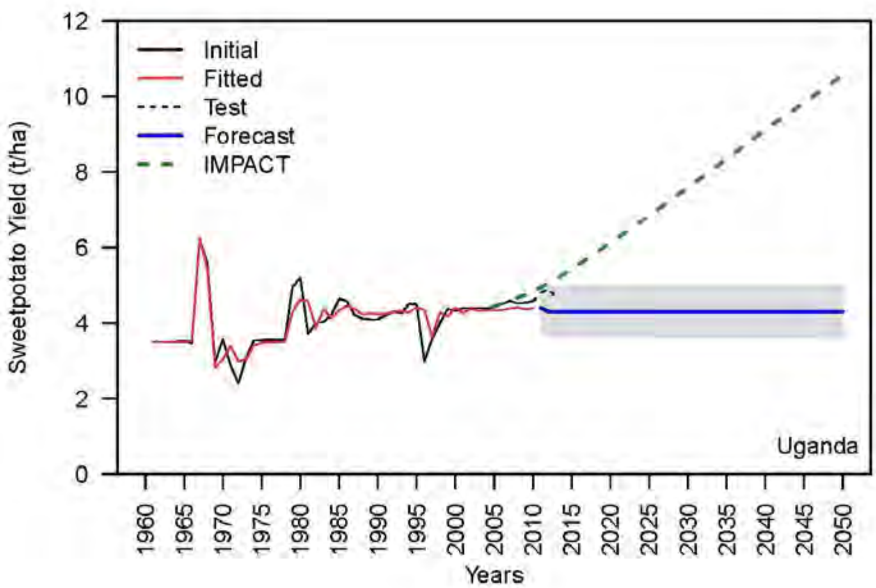


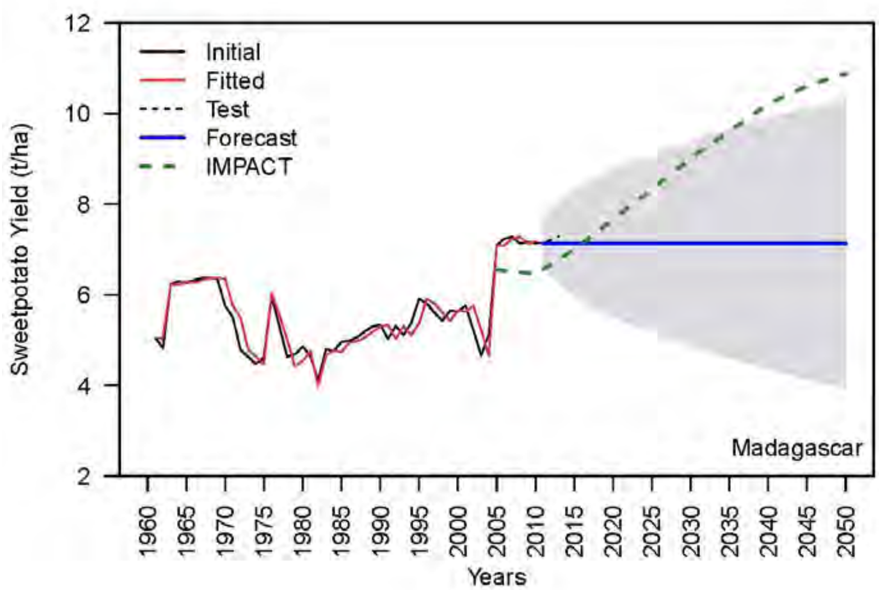
Figure 4.9. Sweetpotato yield forecast for Uganda.

The analysis of the sweetpotato yield series in Madagascar revealed two level shifts in 1963 and 2005, a temporary change in 1976 and an additive outlier in 1982. The intervention model that gave the lowest AICC score was an ARIMA(0,1,0), i.e., a random walk process:

$$\hat{y}_t - y_{t-1} = 1.400LS_{1963} + 1.410TC_{1976} - 0.594AO_{1982} + 1.960LS_{2005} + \varepsilon_t$$

As can be seen from Figure 4.10, reported FAOSTAT sweetpotato yields in Madagascar have remained constant since 2006, at around 7 tons per ha. The ARIMA model also projects constant yields until 2050 and therefore returns very accurate in-sample forecasts. Yields produced by IMPACT remain constant for 2005-2009 and increase after 2010, but the forecasting accuracy for the entire 2005-2013 period is very poor according to both, the MAPE and MASE measures. These results suggest that IPRs for both sub-periods should be adjusted to better represent the reported FAOSTAT yields. As regards to the post-2014 yield forecasts, IMPACT projects a growth trajectory leading to a final yield of 11 tons per ha in 2050 which, however, lies outside the ARIMA prediction interval. An "average" scenario of productivity growth therefore translates to a yield of around 9 tons per ha in 2050.

Figure 4.10. Sweetpotato yield forecast for Madagascar.



Finally, the sweetpotato yield series for Rwanda contains temporary changes in 1963, 1974 and 1989, and additive outliers in 1964, 1965 and 1969. The intervention model selected was the following ARIMA(0,1,0):

$$\hat{y}_t - y_{t-1} = -2.753TC_{1963} - 2.566AO_{1964} - 3.085AO_{1965} - 1.201AO_{1969} + 1.381TC_{1974} - 1.546TC_{1989} + \varepsilon_t$$

IMPACT approximates observed yields for 2005-2009 adequately but, although it projects increasing yields that exceed 12 tons per ha in 2050, it is not able to capture the rapid yield growth recorded in 2010-2013 (Figure 4.11). As an additional control procedure, we examined the entire series (1961-2013) but no statistical evidence was found that this rapid growth after 2010 constitutes any type of outlier. The IPRs for 2010-2014 should therefore be adjusted upwards. Similarly, the ARIMA model also produces very poor in-sample forecasts as it projects constant yields of about 7.5 tons per ha until 2050. Since the yield growth projected by IMPACT lies inside the ARIMA prediction interval, no adjustments are proposed for post-2014 IPRs.

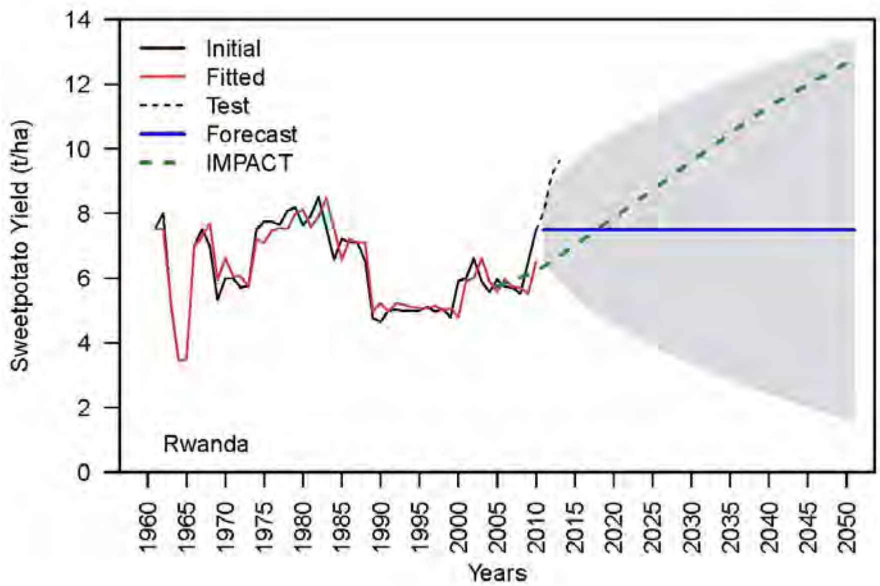


Figure 4.11. Sweetpotato yield forecast for Rwanda.

The statistical analysis of the sweetpotato yield series for the five SSA countries suggests that a level trend is likely to continue in the future but these results should be viewed with caution given the admittedly low reliability of the data. However, although the issue of data quality creates obstacles in understanding the true dynamics behind the evolution of sweetpotato yields in SSA, it is also true that sweetpotato production in the region is more heavily impacted by biotic and abiotic constraints than in other parts of the world. The impact of these factors on both actual yields and yield stability is highly heterogeneous across the continent, and this calls for more region-specific breeding approaches and strategies (Andrade et al., 2009). For this reason, CIP is promoting breeding in a decentralized way through the Sweetpotato Action for Security and Health in Africa (SASHA) network which involves collaboration with National Agricultural Research System (NARS) partners. Although current breeding efforts concentrate mainly on the development of high yielding OFSP varieties as a means to combating vitamin A deficiency (Grüneberg et al., 2015), breeding for disease- and pest-resistant varieties is also needed to reduce the gap between attainable and actual yields.

5. DISCUSSION AND CONCLUSIONS

In this paper we estimate ARIMA models as a means to forecast future yields for potatoes and sweetpotatoes in the world's ten biggest producing countries in order to review the yield projections produced by the IMPACT partial equilibrium model and to suggest changes to the IPR parameters in the model. Literature sources are then utilized to assess whether the yield trajectories produced by either the ARIMA model or IMPACT are more likely to be realized, or if none of the above offers a realistic scenario of future productivity growth. When the literature does not provide enough evidence of a likely yield growth trajectory, we use simple rules of thumb based on the prediction intervals which are produced as part of the ARIMA estimation procedure.

The main assumption of the statistical analysis is that yields constitute a random process which exhibits deterministic and/or stochastic trends (components) which incorporate the effect of all factors that determine yield growth in the long term and may not be adequately represented by simpler statistical models. This means that the selected statistical model is void of economic content because no exogenous variables are explicitly considered. A second assumption is that the framework of the analysis will not change in the future, i.e., climate and socioeconomic conditions will not deviate from their current average trend. We can thus characterize the ARIMA yield forecasts as the outcome of a "middle of the road" pathway under no specific climate change scenario. Even under this assumption, however, the question of whether historical yields can provide information about future crop productivity cannot be answered by this exercise. In this sense we do not claim to "predict" future yields but rather to trace a potential trajectory, given the historical data available. In fact, forecasting future yields can be decomposed in two distinct parts; (i) the estimation of the final yield in 2050 and (ii) the path followed to reach this yield. Since the ARIMA model produces a linear growth trend, it is not possible to propose different growth rates in each five-year period and therefore only the final yield in 2050 can be evaluated using literature sources. Because we have assumed that yields depend exclusively on their past values and on the errors (deviations) around a deterministic trend, we can only account for the uncertainty in our projections with prediction intervals which incorporate the uncertainty of the error terms. Note that the prediction intervals estimated in statistical packages from ARIMA-based models tend to be narrower than what they really are because many sources of uncertainty are not considered, especially the variation in the parameter estimates (Hyndman et al., 2002).

Although we have used two statistical measures to evaluate the accuracy of the in-sample ARIMA forecasts as a simple test for the overall validity of the estimated models, our experience clearly shows that accurate results for the test period are not necessarily evidence of a "good" forecasting model and, equivalently, low accuracy is not evidence of a "bad" model. For example, the ARIMA model does not produce accurate in-sample forecasts for potato yields in India, yet the long term yield projections are in line with what is inferred from the related literature and also with the objective of the Indian government to increase yields by 2050 at a level similar to the ARIMA forecasts.

At the same time the validity of any model depends directly on the data used for estimation. For statistical forecasting models, this argument gives rise to several issues: first, the number of observations in our "training" sub-sample is rather small (50 out of 53 observations in the FAOSTAT database), yet we consider it to be of adequate size for a characterization of an ARIMA process. Still, a larger sample would definitely provide more information on the random process as was clearly seen in several cases (e.g. potato yields in Poland), where the consideration of the entire series (1961-2013) resulted in the estimation of a different model than the one produced with only the "training" sub-sample (1961-2010).

The second important issue is the low quality of data which appears to be more pronounced in SSA countries but is not restricted to sweetpotato. For example, Scott and Suarez (2012b) report that China has been revising its national statistics regarding potato production, while Scott et al. (2013) question the reliability of FAOSTAT data for potato production in Southern Africa. The data reliability problem has significant implications on every part of the analysis, as it may lead to biased coefficients in the ARIMA model and to the identification of multiple outliers, especially level shifts, even though there is no apparent reason for such structural changes in the yield series. Indeed, we were unable to provide an explanation for most outliers found in the yield series in the countries under examination. As regards to the IMPACT model, erroneous yield data may wrongly provide evidence that IPR adjustments are needed and can mask growth trends or wrongly suggest their existence. Finally, another limitation of FAOSTAT data is that no distinction can be made between irrigated and rainfed crop yields, although in some cases it is evident that production is dominated by a specific production system (like sweetpotato production in SSA is considered to be almost entirely rainfed). As a result, the ARIMA yield forecasts refer to average national yields that include the effect of both irrigated and rainfed systems.

Despite the above problems, we argue that the analysis of the yield time series is indeed the only practical way of calibrating exogenous parameters in global economic models, such as IPRs in IMPACT. Although we have chosen ARIMA processes to characterize past yields and to forecast future productivity growth trends, other models can be used for this purpose as well. For example, an interesting alternative that can also induce notions of sensitivity (scenario) analysis would be to examine how different parameters, which tend to vary with each Shared Socioeconomic Pathway (SSP), affect the projected yield growth rates. The task would be therefore to determine the correlation between yield trends and the IMPACT parameters that are SSP-specific, namely GDP and population growth. Note that a similar approach is followed in the case of the GLOBIOM model which also contains an exogenous trend component attributed to technological progress in crop improvement (Havlík et al., 2014). This trend is econometrically estimated by regressing historical crop yields against GDP per capita and the estimated yield are then projected in the future using the GDP per capita forecasts for different SSPs.

The most appropriate way to forecast future yield trends would be in fact to use simultaneously different statistical (or other) models which complement each another in a manner similar to the default IMPACT results and the ARIMA prediction intervals in the present exercise. The obvious advantage of combing different models is that the general direction of change (growth or decline) will become more obvious and its characterization more robust since different models use different assumptions and estimation approaches. Still, any forecasting method must be able to identify and account for data quality problems like the ones in the historical yield series which were described in the previous paragraphs. In this respect, the methodology used in this paper and the results obtained for potato and sweetpotato can provide an interesting starting point for developing a methodological framework which will utilize different statistical tools to determine future values for parameters for all crops in the GFSF project.

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APPENDIX A: OUTLIERS AND ADJUSTMENTS IN POTATO YIELD SERIES

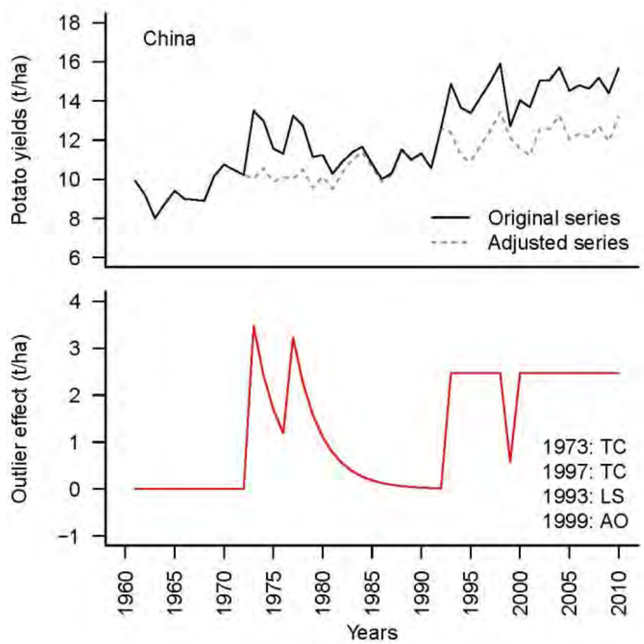


Figure A.1. Outliers of the potato yield series in China.

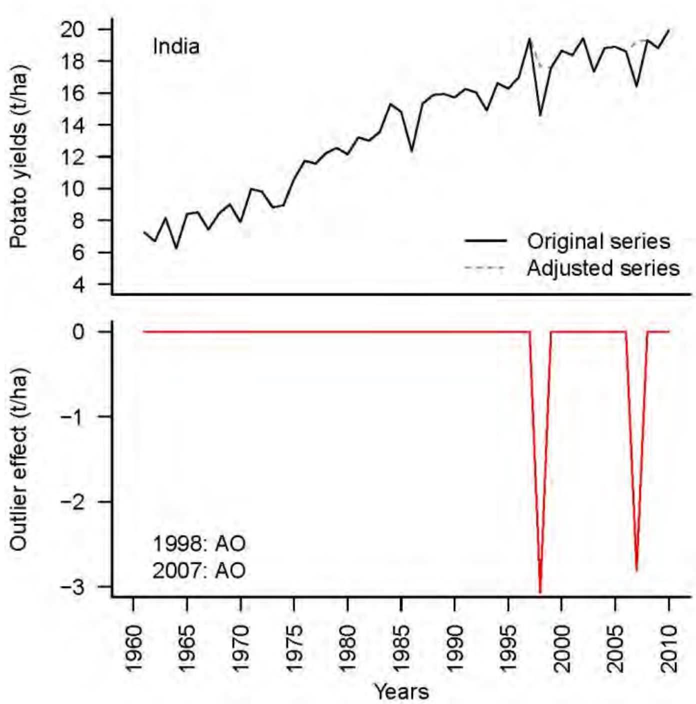


Figure A.2. Outliers of the potato yield series in India.

Figure A.3. Outliers of the potato yield series in the United States.

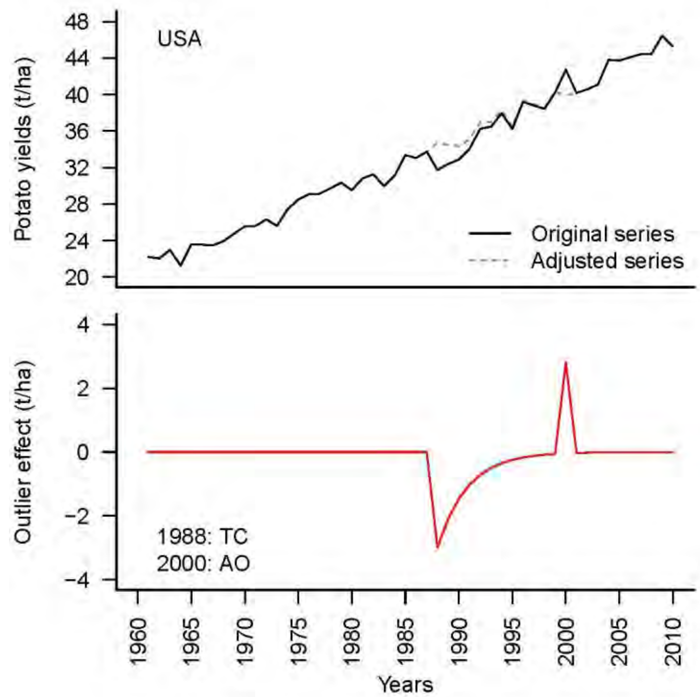
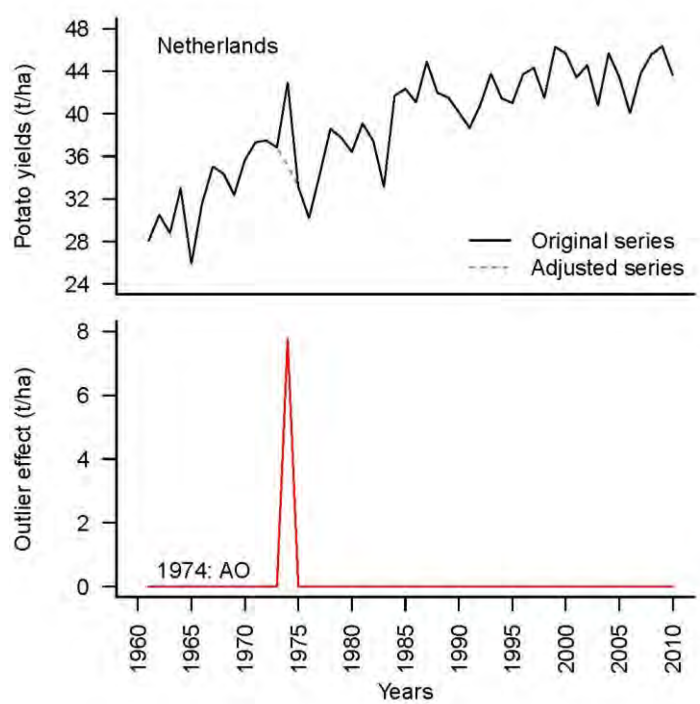


Figure A.4. Outliers of the potato yield series in the Netherlands.



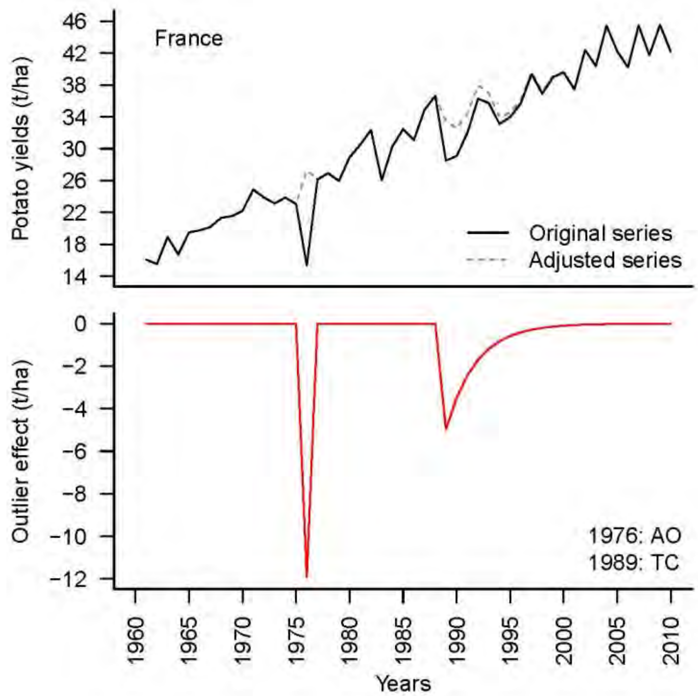


Figure A.5. Outliers of the potato yield series in France.

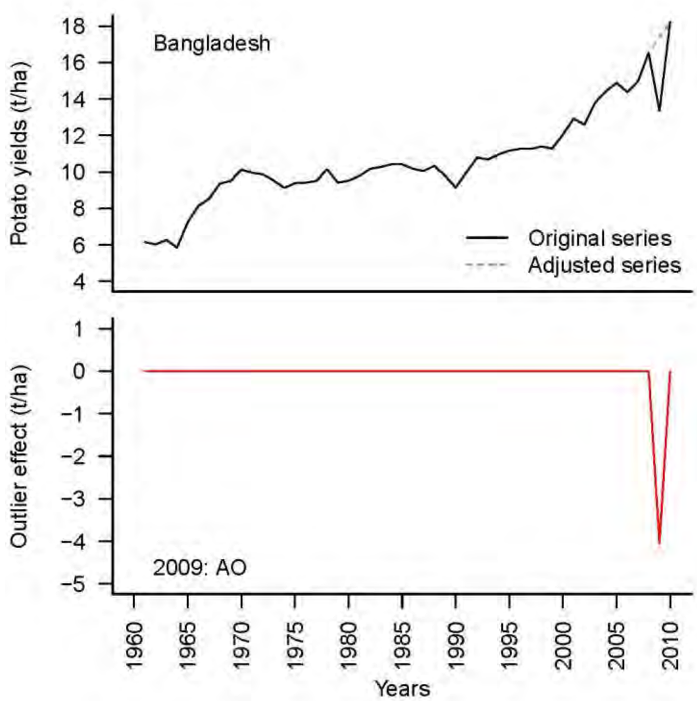


Figure A.6. Outliers of the potato yield series in Bangladesh.

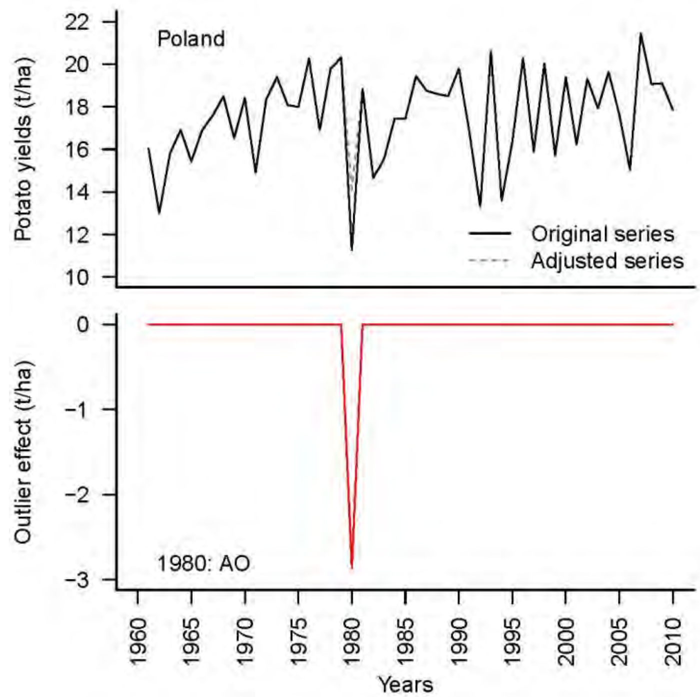


Figure A.7. Outliers of the potato yield series in Poland using 1961-2010 data.

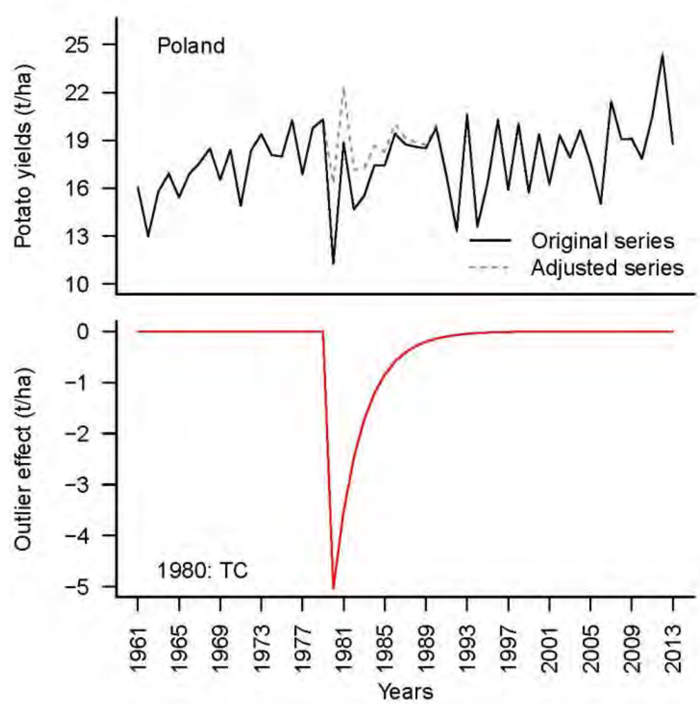


Figure A.8. Outliers of the potato yield series in Poland using 1961-2013 data.

APPENDIX B: OUTLIERS AND ADJUSTMENTS IN SWEETPOTATO YIELD SERIES

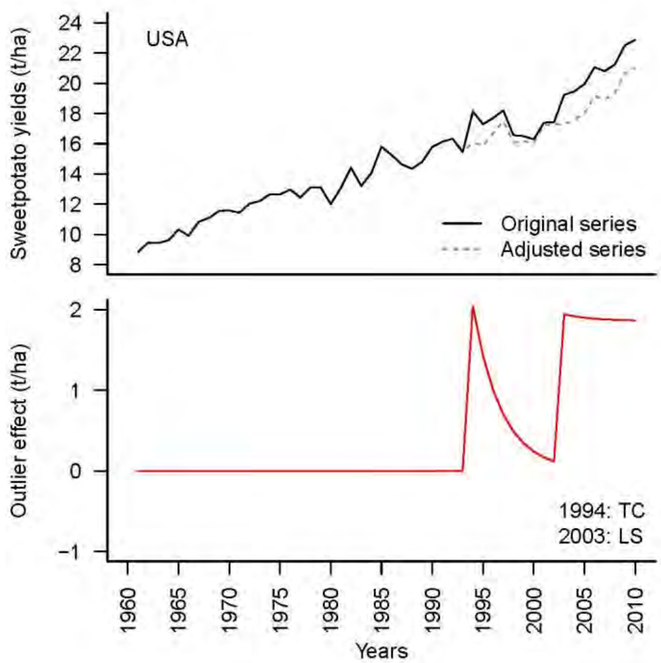


Figure B.1. Outliers of the sweetpotato yield series in the United States.

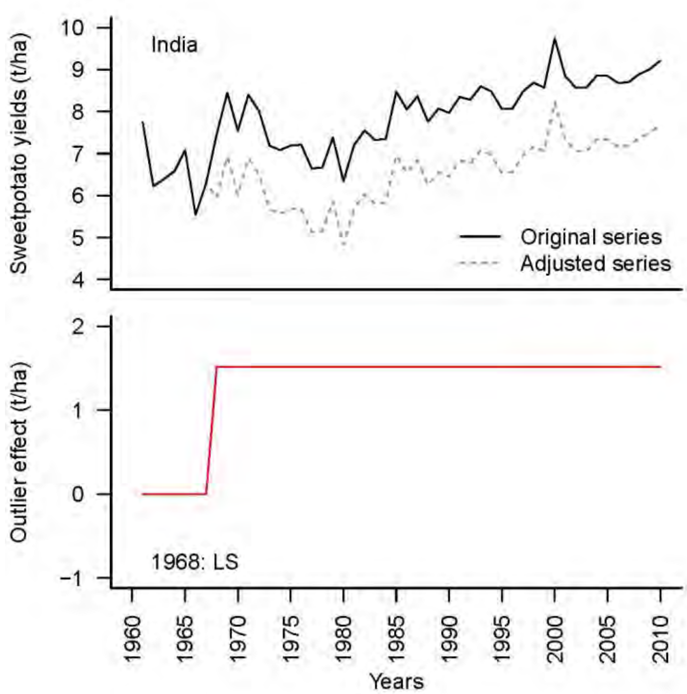


Figure B.2. Outliers of the sweetpotato yield series in India.

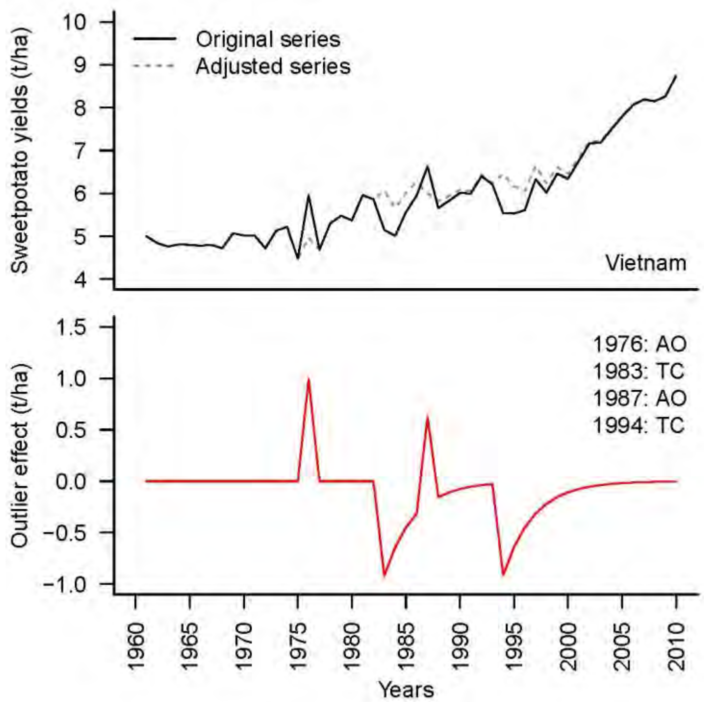


Figure B.3. Outliers of the sweetpotato yield series in Vietnam.

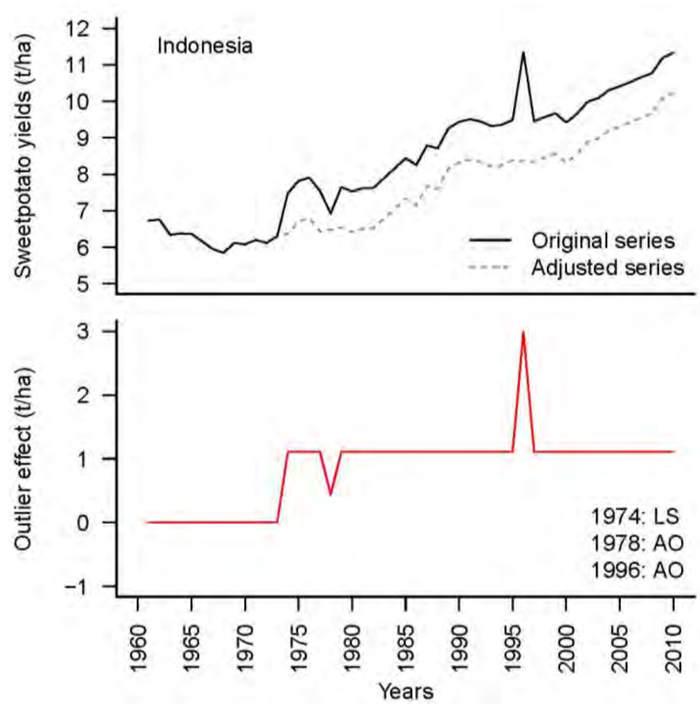


Figure B.4. Outliers of the sweetpotato yield series in Indonesia.

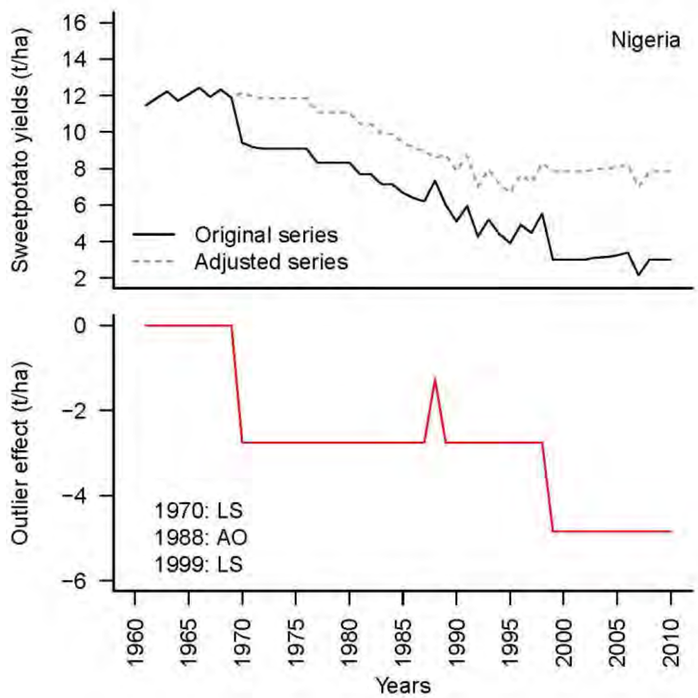


Figure B.5. Outliers of the sweetpotato yield series in Nigeria.

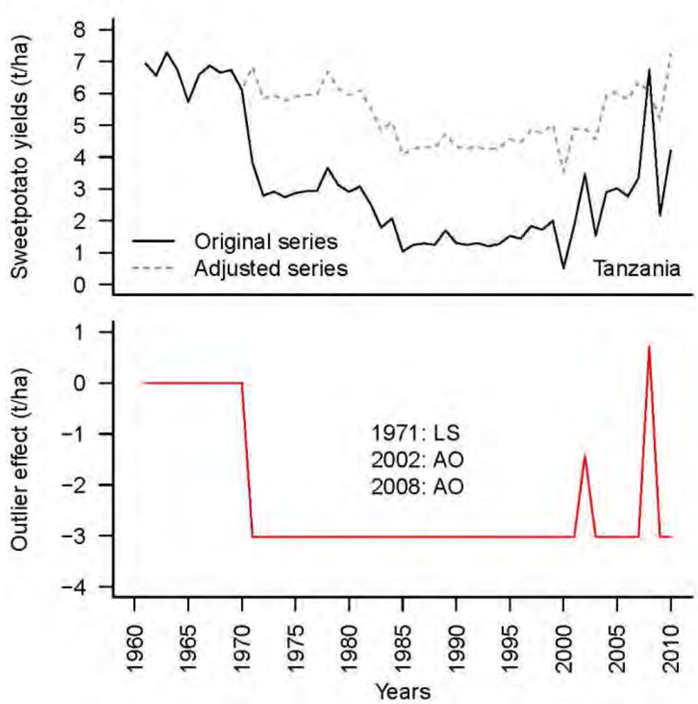


Figure B.6. Outliers of the sweetpotato yield series in Tanzania.

Figure B.7. Outliers of the sweetpotato yield series in Uganda.

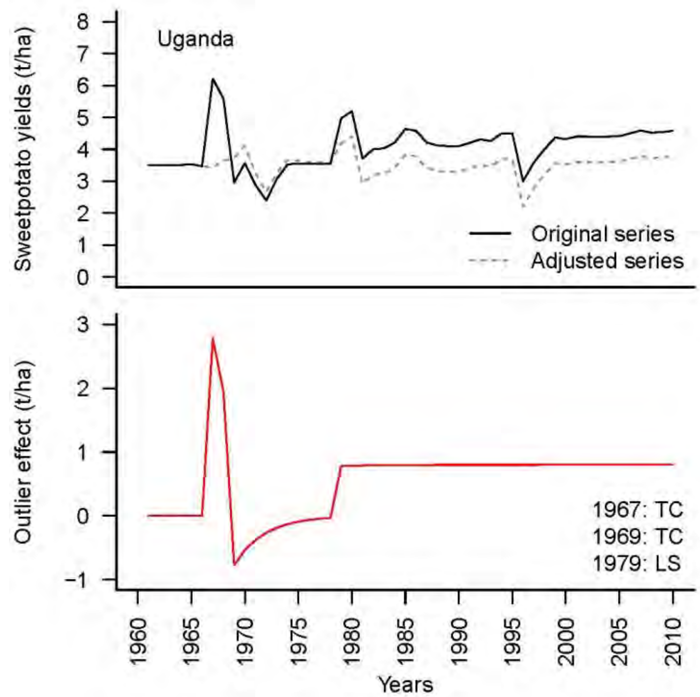
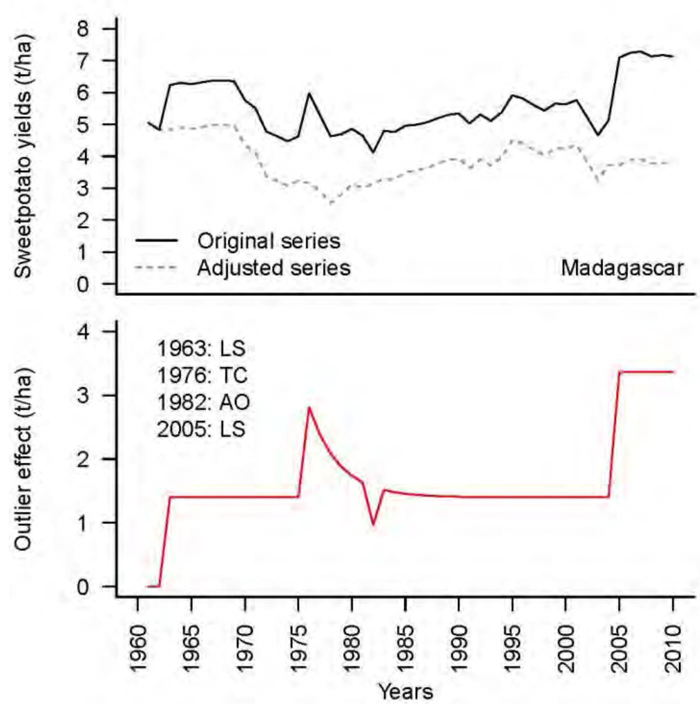


Figure B.8. Outliers of the sweetpotato yield series in Madagascar.



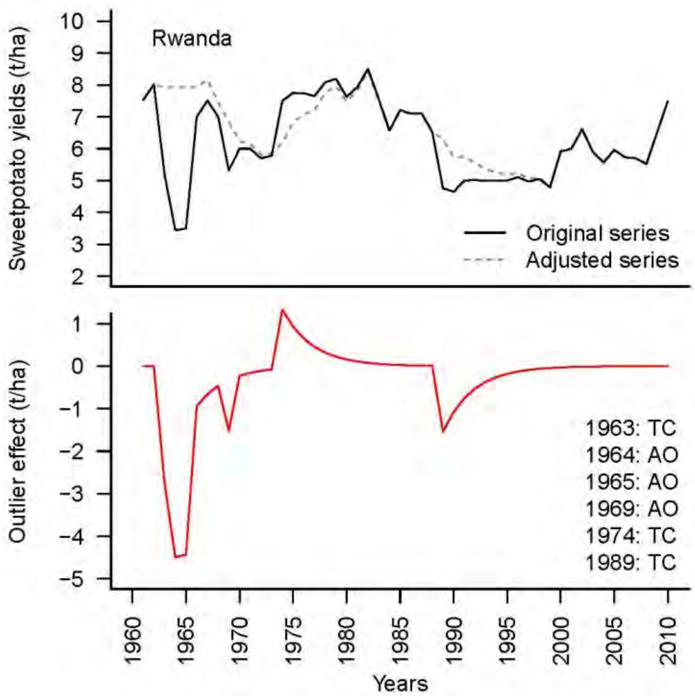


Figure B.9. Outliers of the sweetpotato yield series in Rwanda.

APPENDIX C: SUMMARY OF STATISTICAL MODELS ESTIMATED

Table C1: Statistical models for potato yield forecasts

Country	Statistical Model
China	$\hat{y}_t - y_{t-1} = 0.074 - 0.359y_{t-1} - 0.338y_{t-2} - 0.658y_{t-3} + 3.466TC_{1973} + 2.394TC_{1977} + 2.462LS_{1993} - 1.888AO_{1999} + \varepsilon_t$
India	$\hat{y}_t - y_{t-1} = 0.267 - 3.071AO_{1998} - 2.807AO_{2007} + \varepsilon_t - 0.759\varepsilon_{t-1}$
Russia	$\hat{y}_t = 9.677 + 192t - 3.419AO_{2010}$
Ukraine	$\hat{y}_t = 9.674 + 0.243t$
United States	$\hat{y}_t - y_{t-1} = 0.488 - 0.661y_{t-1} - 0.330y_{t-2} - 2.988TC_{1998} + 2.851AO_{2000} + \varepsilon_t$
Germany	$\hat{y}_t - y_{t-1} = 0.456 + \varepsilon_t - 0.665\varepsilon_{t-1}$
Netherlands	$\hat{y}_t - y_{t-1} = 0.318 + 7.760AO_{1974} + \varepsilon_t - 0.796\varepsilon_{t-1}$
France	$\hat{y}_t - y_{t-1} = 0.572 - 0.922y_{t-1} - 0.785y_{t-2} - 0.652y_{t-3} - 0.472y_{t-4} - 11.916AO_{1976} - 4.973AO_{1989} + \varepsilon_t$
Bangladesh	$\hat{y}_t - y_{t-1} = 0.247 - 4.045AO_{1989} + \varepsilon_t$
Poland (1961-2010)	$\hat{y}_t = 17.657 - 6.397AO_{1980} + \varepsilon_t$
Poland (1961-2013)	$\hat{y}_t - y_{t-1} = -0.397y_{t-1} - 5.038TC_{1980} + \varepsilon_t - 0.654\varepsilon_{t-1}$

Table C2: Statistical models for sweetpotato yield forecasts

Country	Statistical Model
China	$\hat{y}_t - y_{t-1} = 0.286 - 0.583y_{t-1} - 0.334y_{t-2} + \varepsilon_t$
Nigeria	$\hat{y}_t - y_{t-1} = -0.551y_{t-1} - 2.756LS_{1970} + 1.490AO_{1988} - 2.086LS_{1999} + \varepsilon_t$
Tanzania	$\hat{y}_t - y_{t-1} = -3.027LS_{1971} + 1.606AO_{2002} + 3.735AO_{2008} + \varepsilon_t - 0.465\varepsilon_{t-1}$
Uganda	$\hat{y}_t = 3.508 + 2.771TC_{1967} - 2.130TC_{1969} + 0.800LS_{1979} + \varepsilon_t$
Indonesia	$\hat{y}_t - y_{t-1} = 0.071 + 1.109LS_{1978} - 0.665AO_{1978} + 1.880AO_{1996} + \varepsilon_t$
Vietnam	$\hat{y}_t - y_{t-1} = 0.075 - 0.425y_{t-1} + 0.995AO_{1976} - 0.918TC_{1983} + 0.848AO_{1987} - 0.896TC_{1994} + \varepsilon_t$
United States	$\hat{y}_t - y_{t-1} = 0.238 + 2.043TC_{1994} + 1.859LS_{2003} + \varepsilon_t - 0.516\varepsilon_{t-1}$
Madagascar	$\hat{y}_t - y_{t-1} = 1.400LS_{1963} + 1.410TC_{1976} - 0.594AO_{1982} + 1.960LS_{2005} + \varepsilon_t$
India	$\hat{y}_t - y_{t-1} = 1.516LS_{1968} + 1.859LS_{2003} + \varepsilon_t - 0.563\varepsilon_{t-1}$
Rwanda	$\hat{y}_t - y_{t-1} = -2.753TC_{1963} - 2.566AO_{1964} - 3.085AO_{1965} - 1.201AO_{1969} + 1.381TC_{1974} - 1.546TC_{1989} + \varepsilon_t$

APPENDIX D: RESULT SUMMARY OF POTATO YIELD FORECASTS

Table D1: Result summary for potato yield forecasts in China.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	8.4%	1.64	Inaccurate in-sample forecasts: FAOSTAT yields are outside of the 95% prediction interval.
IMPACT (2005-2009)	1.8%	0.25	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	7.7%	2.72	Inaccurate in-sample forecasts: IPRs should be adjusted upwards.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.51%	18.2 t/ha	Final projected yield in 2050 in line with the literature but yields of around 20 t/ha are also possible.
IMPACT	0.05%	15.7 t/ha	IPRs should be adjusted to reproduce a yield of around 20 t/ ha in 2050.

Table D2: Result summary for potato yield forecasts in India.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	8.8%	1.74	Inaccurate in-sample forecasts: FAOSTAT yields are outside of the 95% prediction interval.
IMPACT (2005-2009)	3.8%	0.28	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	12.2%	1.70	Inaccurate in-sample forecasts: IPRs should be adjusted upwards.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	1.03%	30.6 t/ha	Final projected yield in 2050 in line with the literature.
IMPACT	0.46%	23.0 t/ha	IPRs should be adjusted to reproduce a yield of around 30 t/ha in 2050.

Table D3: Result summary for potato yield forecasts in Russia.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
-	-	-	Linear trend model estimated for the entire series because of small sample size.
IMPACT (2005-2009)	4.3%	0.27	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	12.8%	0.62	Accurate in-sample forecasts: high MAPE score is the result of the volatility of the series. No IPR adjustments required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
Linear trend model	-	21.0 t/ha	Final projected yield in 2050 in line with the literature.
IMPACT	0.10%	13.9 t/ha	IPRs should be adjusted to reproduce the 2050 yield forecast of the linear model.

Table D4: Result summary for potato yield forecasts in Ukraine.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
-	-	-	Linear trend model estimated for the entire series because of small sample size.
IMPACT (2005-2009)	3.5%	0.66	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	8.8%	0.92	Accurate in-sample forecasts: high MAPE score is the result of the volatility of the series. No IPR adjustments required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
Linear trend model	-	24.0 t/ha	Uncertainty due to the current political situation.
IMPACT	0.33%	17.2 t/ha	The growth suggested by IMPACT seems reasonable. No IPR adjustments are proposed.

Table D5: Result summary for potato yield forecasts in the United States.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	2.5%	1.12	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	0.9%	0.25	Accurate in-sample forecasts: no IPR adjustments
IMPACT (2010-2013)	1.5%	2.72	required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.86%	65.4 t/ha	IPRs should be adjusted to represent an average
IMPACT	0.21%	48.9 t/ha	scenario of yield growth, corresponding to a final
			yield of around 57 t/ha in 2050

Table D6: Result summary for potato yield forecasts in Germany.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	6.4%	0.82	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	6.4%	0.47	Accurate in-sample forecasts: no IPR adjustments
IMPACT (2010-2013)	6.1%	0.69	required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.87%	60.9 t/ha	No IPR adjustments are proposed. IMPACT yield
IMPACT	0.81%	56.0 t/ha	projections lie inside the ARIMA 95% prediction
			interval.

Table D7: Result summary for potato yield forecasts in the Netherlands.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	2.8%	0.45	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	4.4%	0.60	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	2.8%	0.79	
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.60%	58.0 t/ha	No IPR adjustments are proposed. IMPACT yield projections lie inside the ARIMA 95% prediction interval.
IMPACT	0.39%	50.4 t/ha	

Table D8: Result summary for potato yield forecasts in France.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	7.6%	1.24	Inaccurate in-sample forecasts but FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	4.1%	0.36	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	5.3%	0.53	
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	1.03%	67.0 t/ha	IPRs should be adjusted to represent an average scenario of yield growth, corresponding to a final yield of around 58 t/ha in 2050
IMPACT	0.26%	49.0 t/ha	

Table D9: Result summary for potato yield forecasts in Bangladesh.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	2.0%	0.65	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	5.8%	0.24	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	14.1%	5.52	Inaccurate in-sample forecasts: IPRs should be adjusted upwards.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	1.04%	28.1 t/ha	Final projected yield in 2050 in line with the literature.
IMPACT	0.76%	21.8 t/ha	IPRs should be adjusted to reproduce a yield of around 28 tons per ha in 2050.

Table D10: Result summary for potato yield forecasts in Poland.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	15.8%	1.34	Inaccurate in-sample forecasts: FAOSTAT yields are partially outside of the 95% prediction interval.
IMPACT (2005-2009)	8.8%	0.38	Accurate in-sample forecasts: high MAPE is the result of the volatility of the series. No IPR adjustments required.
IMPACT (2010-2013)	9.1%	0.51	Accurate in-sample forecasts: high MAPE is the result of the volatility of the series. No IPR adjustments required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	17.7 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	-0.02%	19.1 t/ha	IPRs should be adjusted to reproduce a yield of around 30 tons per ha in 2050.

APPENDIX E: RESULT SUMMARY OF SWEETPOTATO YIELD FORECASTS

Table E1: Result summary for sweetpotato yield forecasts in China.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	2.8%	0.62	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	4.4%	0.94	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	9.2%	4.50	Inaccurate in-sample forecasts: IPRs should be adjusted downwards.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	1.04%	32.7 t/ha	Final projected yield in 2050 in line with the literature.
IMPACT	0.36%	27.0 t/ha	IPRs should be adjusted to reproduce a yield of around 33 tons per ha in 2050.

Table E2: Result summary for sweetpotato yield forecasts in the United States.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	3.3%	1.24	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	1.6%	0.30	Accurate in-sample forecasts: no IPR adjustments
IMPACT (2010-2013)	2.8%	1.19	required.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.85%	32.0 t/ha	Exponential growth seems unreasonable: IPRs
IMPACT	1.89%	47.3 t/ha	should be adjusted to represent an average yield growth scenario of around 39-40 t/ha in 2050.

Table E3: Result summary for sweetpotato yield forecasts in India.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	6.8%	1.48	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	1.6%	0.84	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	2.1%	0.67	
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	9.0 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	0.90%	13.6 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 11-12 t/ha in 2050.

Table E4: Result summary for sweetpotato yield forecasts in Vietnam.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	10.4%	3.16	Inaccurate in-sample forecasts: FAOSTAT yields are outside of the 95% prediction interval.
IMPACT (2005-2009)	1.6%	0.38	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	5.6%	1.22	
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.73%	11.6 t/ha	No IPR adjustments are proposed. IMPACT yield projections lie inside the ARIMA 95% prediction interval.
IMPACT	0.91%	13.0 t/ha	

Table E5: Result summary for sweetpotato yield forecasts in Indonesia.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	15.6%	7.62	Inaccurate in-sample forecasts: FAOSTAT yields are outside of the 95% prediction interval.
IMPACT (2005-2009)	0.8%	0.28	Accurate in-sample forecasts: no IPR adjustments required.
IMPACT (2010-2013)	10.3%	1.27	Inaccurate in-sample forecasts: IPRs should be adjusted upwards. However statistical tests indicate that yields during this period are possibly outliers.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0.54%	14.2 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 15-16 t/ha in 2050.
IMPACT	0.91%	16.9 t/ha	

Table E6: Result summary for sweetpotato yield forecasts in Nigeria.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	1.4%	0.09	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	21.4%	0.72	Inaccurate in-sample forecasts: Although the MASE score is low, IMPACT yields trend upwards. IPRs should be adjusted downwards but data quality is questionable.
IMPACT (2010-2013)	33.1%	37.52	Inaccurate in-sample forecasts: IPRs should be adjusted downwards but data quality is questionable.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	3.0 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	0.36%	10.8 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 6-7 t/ha in 2050.

Table E7: Result summary for sweetpotato yield forecasts in Tanzania.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	26.6%	1.82	Inaccurate in-sample forecasts: FAOSTAT yields are partially outside of the 95% prediction interval.
IMPACT (2005-2009)	23.9%	0.29	Accurate in-sample forecasts: high MAPE score is the result of the volatility of the series. No IPR adjustments required but data quality is questionable.
IMPACT (2010-2013)	25.9%	2.24	Inaccurate in-sample forecasts: IPRs should be adjusted upwards but data quality is questionable.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	3.5 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	2.32%	8.5 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 6 t/ha in 2050.

Table E8: Result summary for sweetpotato yield forecasts in Uganda.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	9.6%	1.30	Inaccurate in-sample forecasts but FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	1.7%	0.75	Accurate in-sample forecasts: no IPR adjustments
IMPACT (2010-2013)	5.3%	1.46	required but data quality is questionable.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	4.3 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	1.90%	10.6 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 7.5 t/ha in 2050.

Table E9: Result summary for sweetpotato yield forecasts in Madagascar.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	1.2%	0.29	Accurate in-sample forecasts: FAOSTAT yields are inside the 95% prediction interval.
IMPACT (2005-2009)	9.3%	4.54	Inaccurate in-sample forecasts: IPRs should be
IMPACT (2010-2013)	8.0%	10.46	adjusted upwards but data quality is questionable.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	7.1 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	1.25%	10.9 t/ha	IPRs should be adjusted to represent an average yield growth scenario of around 9 t/ha in 2050.

Table E10: Result summary for sweetpotato yield forecasts in Rwanda.

In-sample forecasts			
Model	**MAPE**	**MASE**	**Comment**
ARIMA	15.9%	2.54	Inaccurate in-sample forecasts: FAOSTAT yields are outside of the 95% prediction interval but data quality is questionable.
IMPACT (2005-2009)	5.0%	0.94	Accurate in-sample forecasts: no IPR adjustments required but data quality is questionable.
IMPACT (2010-2013)	24.4%	3.02	Inaccurate in-sample forecasts: IPRs should be adjusted upwards but data quality is questionable.
Out-of-sample forecasts			
Model	**CAGR**	**2050 yield**	**Comment**
ARIMA	0%	7.5 t/ha	The ARIMA model produces a level yield forecast.
IMPACT	1.70%	12.7 t/ha	No IPR adjustments are proposed. IMPACT yield projections lie inside the ARIMA 95% prediction interval.

The International Potato Center (known by its Spanish acronym CIP) is a research-for-development organization with a focus on potato, sweetpotato, and Andean roots and tubers. CIP is dedicated to delivering sustainable science-based solutions to the pressing world issues of hunger, poverty, gender equity, climate change and the preservation of our Earth's fragile biodiversity and natural resources.
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