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Fertilizer and grain prices constrain food production in sub-Saharan Africa

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Crop yields across sub-Saharan Africa are much lower than what is attainable given the environmental conditions and available technologies. Closing this 'ecological yield gap' is considered an important food security and rural welfare goal. It is not clear, however, whether it is economically sensible for farmers to substantially increase crop yields. Here we estimate the local yield response of maize to fertilizer across sub-Saharan Africa with an empirical machine-learning model based on 12,081 trial observations and with a mechanistic model. We show that the average 'economic yield gap'—the difference between current yield and profit-maximizing yield—is about one-quarter of the ecological yield gap. Furthermore, although maize yields could be profitably doubled, the economic incentives to do so may be weak. Our findings suggest that agricultural intensification in sub-Saharan Africa could be supported by complementary agronomic approaches to improve soil fertility, lowering the fertilizer cost, and by spatial targeting of fertilizer recommendations.

Crop yields in sub-Saharan Africa (SSA) are generally much lower than elsewhere. For instance, average maize yield in SSA is 1,446 kg ha^{-1}, whereas average global maize yield, excluding SSA, is 5,783 kg ha^{-1} (refs. [1,2]), and increasing agricultural productivity in SSA could improve food security and rural welfare[3–8]. Increasing staple crop yield, the amount produced per unit cropland area, is also considered an important strategy to mitigate crop area expansion, and thus spare land for nature[9]. It is technically possible to strongly increase crop yields in many regions of SSA because there are large 'ecological yield gaps', the differences between the actual crop yields and the crop yields that could be attained given available technology and the soil and weather conditions[3,4]. Reported national average ecological yield gaps for rainfed maize are as high as 4,800 kg ha^{-1} for Tanzania and Burkina Faso and over 9,000 kg ha^{-1} for Nigeria and Ethiopia[10].

To achieve such substantially higher crop yields, farmers would need to intensify their production systems in several ways. While there are different approaches to increase yields, in all cases farmers would need to use much more fertilizer than they currently do[11–13], and it is not clear if and/or where this would be economically sensible from the farmers' perspectives. The profitability of fertilizer use depends on the effective local price of fertilizer and crop outputs, and on the local crop response to fertilizer. Reported maize responses to nitrogen fertilizer across SSA vary between 5 and 53 kg grain per kg N applied (refs. [14–19]), and fertilizer use has been found to be profitable in some regions[20–24], but not in others[25,26], with considerable variation within countries. It is a challenge to generalize such reports because of the spatial variation in input and output prices, as well as in crop responses to fertilizer.

To better understand opportunities for increasing staple food production in SSA through increased use of fertilizers, we evaluated location-specific ecological and economic conditions and how they affect crop responses to and economic returns on fertilizer investments. We compiled high-spatial-resolution data on soils, weather and local prices of fertilizer and maize grain. To predict crop response to fertilizer, we used an empirical machine-learning model derived from 12,081 observations from maize trials in 1,141 unique locations across SSA, and a mechanistic (rule-based) fertilizer response model called QUEFTS. Both models were used to predict maize yield in response to 539 different fertilizer applications combinations of nitrogen (0–200 kg ha^{-1}), phosphorus and potassium (0–100 kg ha^{-1}) for all 9 × 9 km spatial resolution grid cells of maize production in SSA.

Results and discussion

The empirical model explained 70% of the variation in the fertilizer trial data (Supplementary Figs. 2 and 3) whereas the mechanistic model explained only 26%. The empirical model showed a plausible crop response to fertilizer that was stronger than the mechanistic model at low levels of fertility, but the predicted crop response levelled off earlier than the mechanistic model (Fig. 1 and Supplementary Figs. 4 and 5). The maize-area-weighted average predicted yield with no fertilizer was 1,282 kg ha^{-1} for the empirical model and 1,241 kg ha^{-1} for the mechanistic model (Fig. 1). The reported actual maize-area-weighted average yield was 1,723 kg ha^{-1} (ref. [27]). A nitrogen application of 60 kg ha^{-1} increased predicted yields to 3,001 kg ha^{-1} (empirical model) and 2,147 kg ha^{-1} (mechanistic model) (Supplementary Figs. 4 and 5). The correlation between the two models was 0.42 with no application and 0.34 with a nitrogen application of 60 kg ha^{-1}. The average response rate to an nitrogen application of 60 kg ha^{-1} was 29 kg grain per kg N applied for the empirical model and 15 kg grain per kg N applied for the mechanistic model. The two models predicted similar crop responses for much of East Africa (for example, Ethiopia, Kenya, Uganda, Tanzania), but there were large differences in the West African Sahel region where the empirical model predicted a stronger response to nitrogen (Fig. 1). The lower nitrogen response of the mechanistic model in the West African Sahel was associated with a strong sensitivity to low soil phosphorus availability, which has been identified as the major constraint to crop and rangeland productivity in this region[28,29].

The average maize-area-weighted price across SSA of 1 kg of nitrogen (in urea fertilizer) was US$2.49. It was especially low in Kenya (US$1.38) and Ghana (US$1.46), and very high in Burkina

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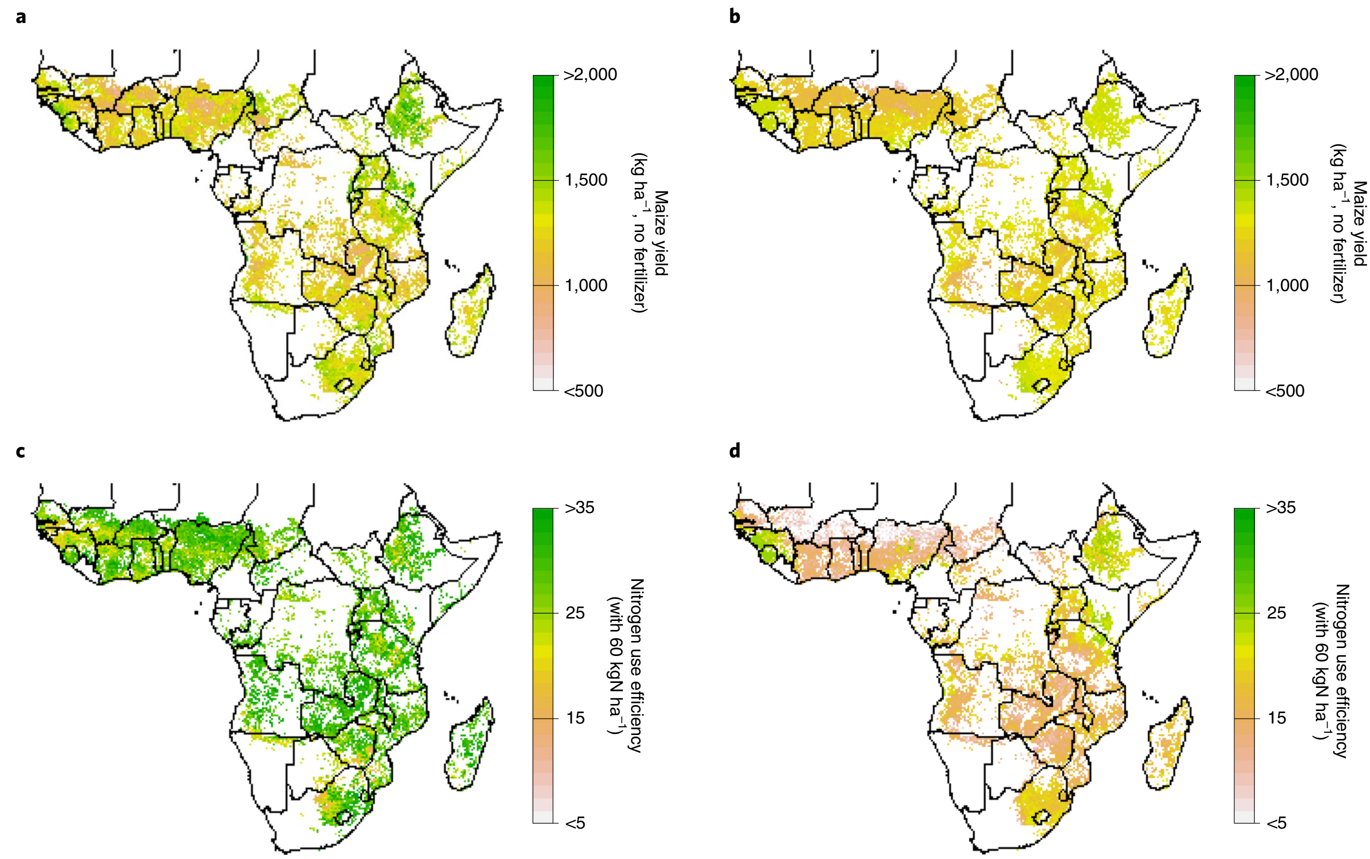

Fig. 1 | Estimated maize yield and nitrogen use efficiency in SSA. a,**b**, Maize yield estimates (kg ha^{-1}) in the absence of fertilizer for maize-producing areas from an empirical (machine learning) model (**a**) and a mechanistic (rule-based) model (**b**). **c**,**d**, Nitrogen use efficiency estimates (kg grain per kg N) for maize-producing areas from an empirical (machine learning) model (**c**) and a mechanistic (rule-based) model (**d**).

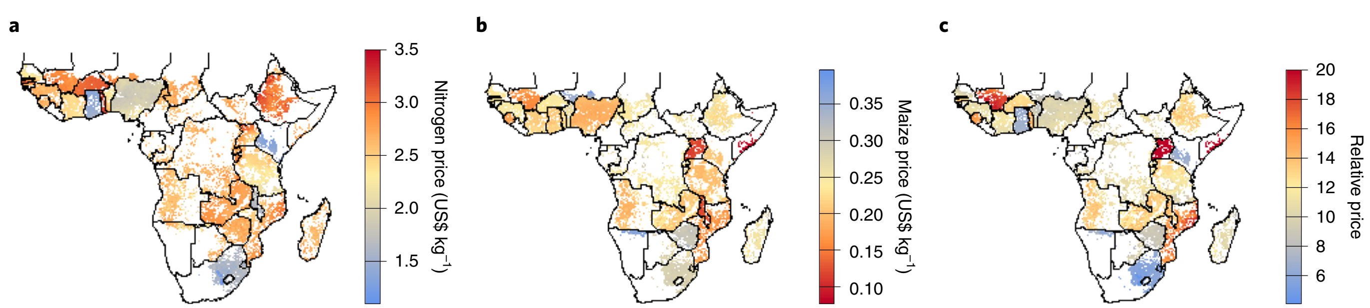

Fig. 2 | Spatial variation in prices in SSA. a, Nitrogen price (US$ kg^{-1}) in urea fertilizer. **b**, Maize price (US$ kg^{-1}). **c**, Relative price (nitrogen price/maize price).

Faso (US$3.05) and Togo (US$3.13). The average price of 1 kg of maize was US$0.23, ranging from US$0.11 in Uganda to US$0.36 in Namibia (Fig. 2). The average nitrogen/maize relative price was 11, that is, the price of 1 kg of nitrogen is equivalent to that of 11 kg of maize. Countries with low nitrogen/maize relative prices (favourable from a fertilizer use perspective) include South Africa (5.6), Kenya (6.6), and Ghana and Namibia (6.9). In contrast, the nitrogen/maize relative prices are very unfavourable in Mali (18) and Uganda (23) (Fig. 2). Prices for other fertilizer products, which also contain potassium and/or phosphorus, were also estimated (Methods).

The empirical model predicted higher maximum profitability (US$344 ha^{-1}) than the mechanistic model (US$88 ha^{-1}) (Fig. 3). The amount of fertilizer needed to achieve maximum profitability ranged from 15 to 245 kg ha^{-1} for the empirical model (average, 93 kg ha^{-1}) and from 0 to 400 kg ha^{-1} for the mechanistic model (average, 72 kg ha^{-1}) (Supplementary Fig. 5). Both models identified areas with relatively high profitable fertilizer applications (>150 kg ha^{-1}) and yields (>5,000 kg ha–) in East Africa (western Ethiopia and western Kenya) and South Africa. The Sahel is an example of a region where the most profitable fertilizer applications were relatively low (<80 kg ha^{-1}) and are associated with more modest maize yields (<3,500 kg ha^{-1}).

The maize-area-weighted mean ecological yield gap was 5,928 kg ha^{-1}. Ecological yield gaps were particularly high in East and Central Africa; in West Africa they were around 4,000 kg ha^{-1}; while in parts of South Africa they were only about 2,000 kg ha^{-1} or less (Supplementary Figs. 6 and 7). On average the economic yield gap—the difference between current yield and the profit-maximizing

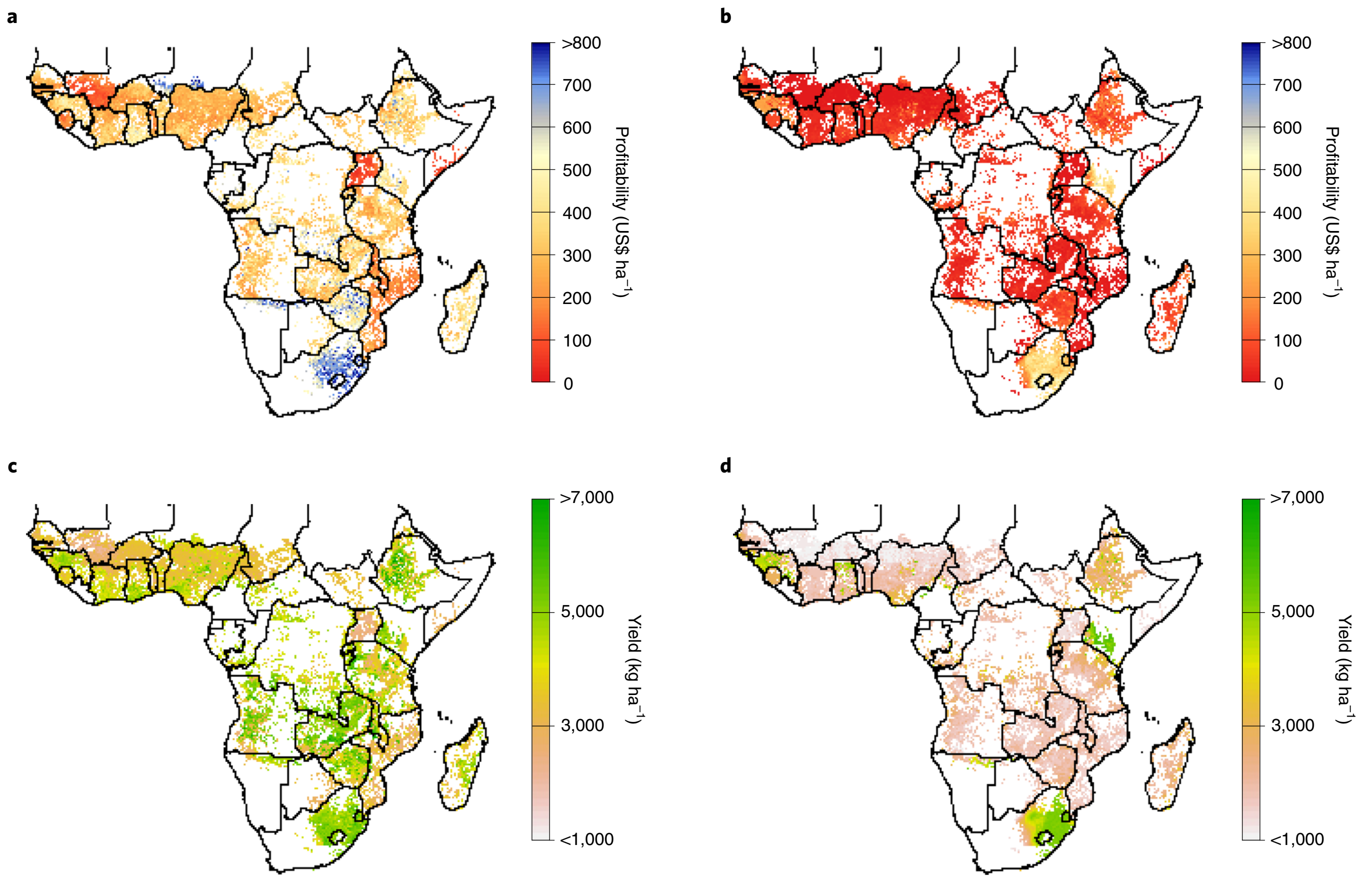

Fig. 3 | Maximum profitability of fertilizer use and maize yield in SSA. a,**b**, Maximum profitability of fertilizer use (US$ ha^{-1}) computed with an empirical (machine learning) model (**a**) and a mechanistic (rule-based) model (**b**) for maize in SSA. **c**,**d**, Maximum maize yield (dry matter, kg ha^{-1}) in SSA computed with an empirical (machine learning) model (**c**) and with a mechanistic (rule-based) model (**d**).

yield—was 27% of the ecological yield gap: 2,309 kg ha^{-1} when computed with the empirical model and 842 kg ha^{-1} with the mechanistic model (Fig. 4a). The difference between the economic and ecologcal yields gaps was small in only few regions, such as South Africa, southern Zimbabwe, southern Ghana and western Kenya (Fig. 4). The average amount of fertilizer required to fill the economic yield gap was 93 kg ha^{-1} (empirical model) and 72 kg ha^{-1} (mechanistic model) (Supplementary Fig. 8).

Depending on the model used, there is no economic yield gap on 8–35% of the maize area in SSA (Fig. 5a). Profits from fertilizer use are likely to be between US$100 and US$300 ha^{-1}, and the relative return of investment (value–cost ratio, VCR) from fertilizer use between 1.5 and 2.5 (Fig. 5b,c). The VCR was computed as the ratio between the benefit of fertilizer use (grain price × increase in grain yield due to the fertilizer application) and the fertilizer cost. The difference in the VCR between the two models is striking, with the empirical model suggesting that VCR > 2 almost everywhere, whereas the mechanistic model suggest that VCR < 2 in most of the continent.

Empirical versus mechanistic models. The differences between the models highlight the importance of research to develop accurate fertilizer response models, whether empirical, mechanistic or a combination of both. The strength of empirical models is that they implicitly consider many factors that mechanistic models do not and are good at predicting within the domain of observations. However, empirical models can produce odd artefacts because of unbalanced data and are not good at extrapolation (for example, predicting yields for very high fertilizer applications that are not observed). Mechanistic models have plausible response curves and interactions, but their strength is explanation rather than prediction[30].

Fertilizer response rates from farm survey data tend to be lower than from experimental data[31,32]. Some of this difference may be due to survey data inaccuracy[33–36], but trials may be biased towards agriculturally favourable areas and reflect systematically better responses on small experimental plots compared with larger fields on actual farms which cannot be managed as intensively[37]. For these reasons, the response rates estimated with the empirical model may be higher than the rates many farmers can realistically achieve. Future work could attempt to build biology-guided empirical learning models by integrating the concepts and general shape of response functions and interactions from a mechanistic model with the flexibility of a machine-learning approach, but progress can only be made if and when more empirical data become available. The open data from the CGIAR[38] enabled the construction of the empirical model, and such initiatives need to be strengthened and expanded to allow for progress to be made in this type of research.

Prices may vary considerably over space[35] and time, seasonally and interannually[39], and it is not obvious how best to account for this temporal variability when modelling economic returns. Even if imperfect, our price estimates are almost certainly more usefully reflective of farmers' economic realities than the common assumptions of spatially constant prices in a country[40]. Prices will also change over time because of changes in the global economy (for example, energy prices) but also in national and regional economies. For example, an increased supply of fertilizer (and/or improved competition in input markets) should drive fertilizer prices down, and increased urban food demand may raise maize prices.

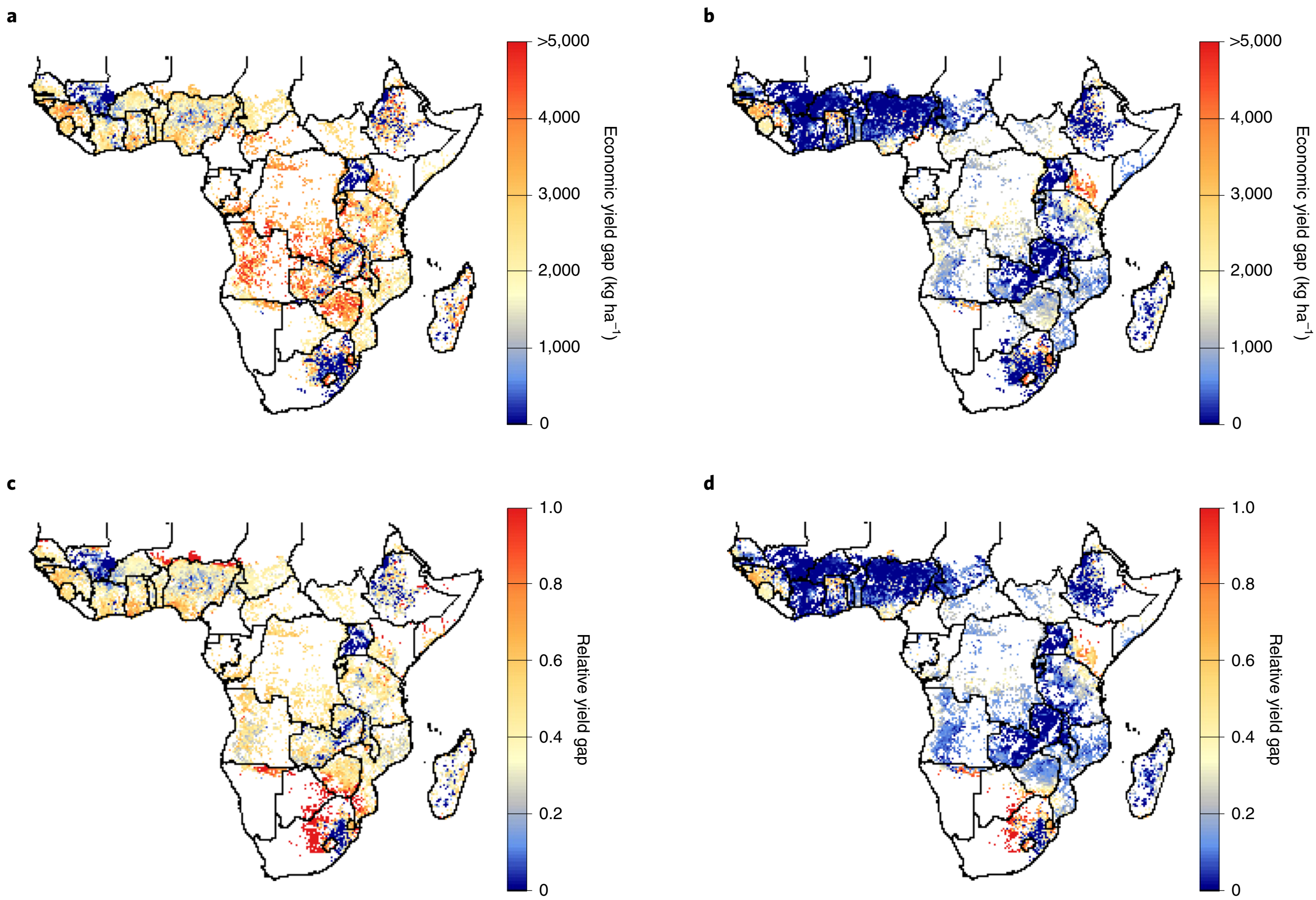

Fig. 4 | Economic and relative yield gaps for maize production in SSA. a,**b**, Economic yield gaps computed with a mechanistic model (**a**) and with an empirical model (**b**). **c**,**d**, Relative yield gaps computed with a mechanistic model (**c**) and with an empirical model (**d**). The economic yield gap ($kg\,ha^{-1}$) is the difference between the maize yield for the most profitable fertilizer treatment and the actual yield. The relative yield gap is the ratio between the economic and ecological yield gaps.

The case for the economic yield gap. While ecological yield gap analysis—the comparison of attainable yield with actual crop yield—is useful for understanding opportunities for agricultural development, under the prevailing conditions it is not a reasonable goal to 'fill the ecological yield gap' in SSA as this would be uneconomic and the large amounts of fertilizer required would have strong negative environmental consequences[13]. Our economic yield gap assessment identifies more realistic upper limits for agriculture intensification. In most regions of SSA, given the crop response to fertilizer, the fertilizer and maize price ratio present a strong barrier to achieving higher yields.

It is likely that our economic yield gaps are somewhat inflated. This is because we did not account for production risk due to interannual rainfall variability or the cost of insurance to protect against that[41]. In some regions, long-term weather forecasts may be a feasible way to help farmers avoid investing too much in fertilizers in years with drought. Furthermore, farmers in remote rural settings generally face less favourable input–output price ratios than farmers in less remote settings[42,43]. While isolation (distance to large cities) was a predictor in our price model, we had insufficient data to estimate the additional 'last-mile' transportation cost of fertilizer from a local market to any given farm location. Estimating effective farm-gate prices is an important goal for future work. Input supply constraints (including late delivery of inputs), limited liquidity at the time of investment and uncertainty about crop outcomes or market conditions (such as output prices at the time of sale) are additional reasons why poor farmers might be reluctant to invest in technologies with positive but relatively small expected returns[7]. The role of risk—in both production outcomes as well as marketing outcomes—is a particularly important factor in the decision-making of risk-averse smallholders[44]. Some kinds of risk may have important spatial dimensions (for example, food price volatility increases with remoteness[45]), which suggests that explicitly modelling uncertainty in returns on production technology over large spatial scales would be a useful area of further analysis. For all the reasons mentioned above, our estimates of profitability are conservative, and the divergence between economic and ecological yield gaps are likely to be even wider.

The effect of the agricultural input subsidy programme in Malawi is an example of how lower costs incentivized greater fertilizer usage which in turn led to crop productivity gains[46]. Such interventions may not be economically feasible, however, or may have unintended negative economic consequences[7]. While other approaches to decreasing fertilizer prices could help—for example, through improving the efficiency of input supply markets—support for the use of mineral fertilizers together with other agronomic practices to improve soil fertility and yield—such as agroforestry and crop rotation, intercropping with legumes or weed management—could be both ecologically and economically prudent[47–49]. For example, while nitrogen fertilizer use will generally increase maize yields, in some regions fertilizer use efficiency can also be improved by introducing more legumes in the cropping system[50,51]. However, the nitrogen

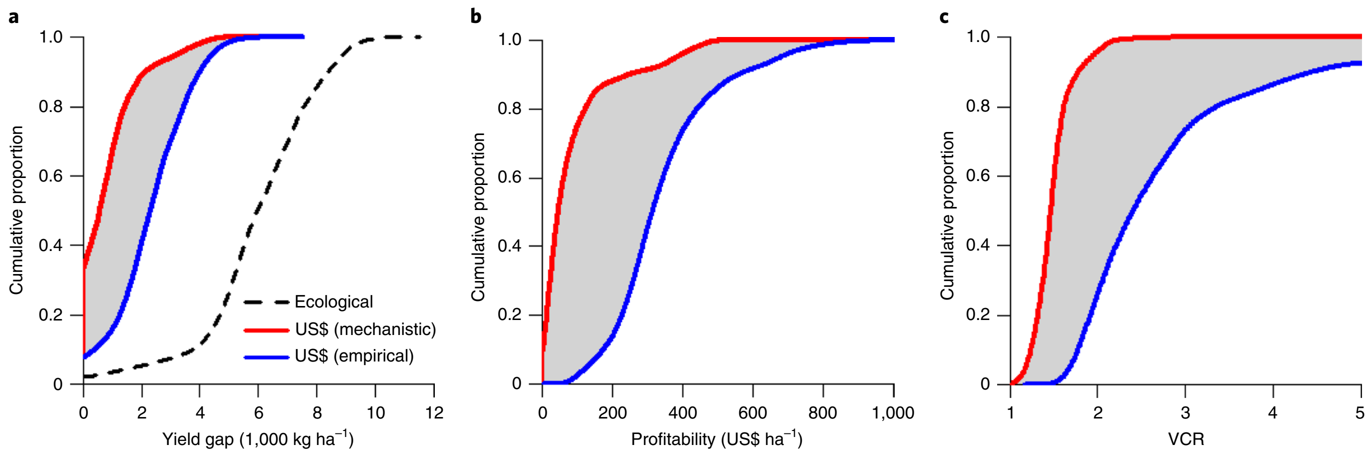

Fig. 5 | Cumulative proportion of the economic and ecological yield gaps, maximum profitability of fertilizer use and the VCR for the most profitable fertilizer use for maize production in SSA. a–c, Cumulative proportion of the economic yield gaps (blue and red lines, representing mechanistic and empirical models, respectively) and the ecological yield gap (black dashed line) (**a**), maximum profitability of fertilizer use (**b**) and the VCR for the most profitable fertilizer use (**c**) for maize production in SSA. The grey shading indicates the area of uncertainty between the empirical and mechanistic models. The VCR was set to 1 if it is not profitable to use any fertilizer.

contribution to other crops from legumes is low in regions with acidic soils with limited phosphorous availability[52]. For these reasons, instead of blanket recommendations for large heterogeneous areas[53,54], fertilizer recommendations could be tailored to small regions and consider localized environmental conditions and variability, prices and agronomic practices. Approaches such as those we develop in this paper can help to guide nutrient management strategies which better reflect heterogeneity in the soil, climatic and economic conditions which affect fertilizer performance and returns on farm-level investments. Agricultural intensification has occurred when it is economically attractive[55] or a necessity[56], but the relatively low economic benefits of staple crop intensification suggest that it is important to compare these to potential gains from other investments, be it on-farm or off-farm[57].

Methods

Empirical model. We built a random forest model of maize yield in response to fertilizer applications and environmental conditions, using the R packages 'randomForest'[58] and 'terra'[59] for the spatial data. To train the model, we compiled a dataset of georeferenced maize observations associated with different levels of fertilizer application. We used the GARDIAN[38] search engine to discover datasets and publications from repositories across the international agricultural research centres of CGIAR and others. Search keywords included Africa fertilizer, maize, fertilizer trials, nitrogen, macronutrient, soil fertility and nutrient omission trials. We compiled 227 datasets that had 12,081 maize yield observations distributed in 1,141 unique locations across SSA (Supplementary Fig. 1 and Supplementary Table 1).

In the model, we used the following predictor variables for the gridded soil properties data: effective root zone depth for maize[60]; soil pH (H_2O); extractable phosphorous content (mg 100 kg^{-1}); and soil organic carbon content (g kg^{-1}) for the 0–30 cm topsoil[61] (Supplementary Table 2). In addition, we used mean annual temperature (°C)[62] and monthly rainfall by year[63]. We used monthly rainfall data for the years that matched the years and growing seasons of the yield data.

Mechanistic model. We used WOFOST[64] implemented in Rwofost[65] to compute water-limited yield (Yw) for maize, as determined by cultivar characteristics, the amount of incoming solar radiation, ambient temperature, carbon dioxide and water supply[66]. We used ERA5-Land daily weather data[63] that we bias-corrected with WorldClim[62] (Supplementary Table 2). The RZ-PAWHC dataset[60] was used as input for soil water balance computation. We modified default crop parameters for the temperature sum (°C d^{-1}) from emergence to anthesis and from anthesis to maturity to simulate a very early (600 and 650 °C d^{-1}), early (700 and 800 °C d^{-1}), medium (800 and 950 °C d^{-1}) and late (900 and 1,000 °C d^{-1}) variety. We ran the model for all soil cells combined with daily weather using an emergence day on the 15th of each month for each of the 18 years (1997–2015). To select a plausible growing season, we computed the average yield for each month, and the maximum of the resulting 12 values was used as the Yw for each variety; that is, for each soil cell we selected the sowing date that on average gave the highest Yw during the 18 yr period. We report the average yield for the best performing variety.

Yield responses to nitrogen, phosphorus and potassium fertilizer applications, given a few soil properties were also estimated with the Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) model[67,68] as implemented in Rquefts[61,69]. QUEFTS was originally developed for maize under rainfed conditions. The model assumed that nitrogen, phosphorus and potassium are the main growth-limiting factors. QUEFTS estimates native soil supply of nitrogen, phosphorus and potassium from soil parameters such as pH and organic matter content. Yield is computed based on an estimate of actual nutrient uptakes and crop nutrient requirements and cannot exceed water-limited yield. We computed the base (unfertilized) soil supply of nitrogen, phosphorus and potassium after calibrating with the zero-fertilizer treatments of the compiled trial data soil chemical properties data from ref. [68] (Supplementary Table 2).

We calibrated the native nutrient supply from soils (in the absence of fertilizers) that QUEFTS uses with the experimental data described above; and we used the default response rate parameters for maize that come with the model. We evaluated the QUEFTS model predictions using the trial data used for the empirical model described above.

Price data. We used a database of fertilizer prices in markets across 18 countries in SSA[35] to predict the fertilizer price in these countries (Supplementary Table 4). As we had most data for urea (a source of inorganic nitrogen), we fitted random forest models of urea prices as a function of longitude, latitude and additional predictor variables that capture aspects of market access (distance to the nearest port; town with over 50,000 inhabitants; town with over 100,000 inhabitants; and town with over 250,000 inhabitants)[70], demand (urban and rural population density)[71], cropland[72] and the environment (annual precipitation)[62] (Supplementary Table 3). The most important variables in the country-level random forest models were latitude and longitude, followed by rural population density, precipitation and population density.

For countries for which we had no market data we built another model by pooling all the data and using all the predictor variables except for location (longitude and latitude). We modelled relative (to the countries' reported average price) urea price within all countries and multiplied that by the reported price to get subnational price variation that matches the average national price. We estimated the price of other fertilizers using linear regression models where the urea price was the sole predictor variable[35]. The slopes (price relative to the urea price) were US$1.20 kg^{-1} for diammonium phosphate, US$1.14 kg^{-1} for triple superphosphate, US$1.03 kg^{-1} for NPK (15–15–15) and US$0.97 kg^{-1} for potassium chloride (Supplementary Fig. 8).

We used a database of cereal prices across 168 markets and 30 countries in SSA compiled by Cedrez et al.[39] (Supplementary Table 5 and Supplementary Fig. 9); and followed their methodology to predict maize price at the beginning of the harvesting season as a function of access to market (travel time to market) and precipitation (Supplementary Table 3). The most important variables were latitude, longitude and precipitation.

Crop response predictions and profitability. We predicted yield responses to 539 different combinations of nutrient applications for each of the 442,156 grid cells with maize. Nitrogen treatments were 0 and from 10 to 100 kg ha^{-1} in six steps of 15 kg ha^{-1}, and from 100 to 200 kg ha^{-1} in four steps of 25 kg ha^{-1}; phosphorous and potassium treatments were 0 and from 10 to 100 kg ha^{-1} in steps of 15 kg ha^{-1}. For each cell, we ran both models 539 times. There were 44,156 cells with maize, thus we had a total of $373{,}013 \times 539 \times 2 = 476{,}644{,}168$ runs. We used the 'fertApp' function from the R package Rquefts to compute, for each fertilizer treatment (for example, 50N–30P–0K), the optimal fertilizer application rates given a target nutrient application, the available fertilizer blends (for example, diammonium phosphate, NPK 15–15–15, potassium chloride, triple superphosphate, urea) and their prices. Finally, we multiplied the computed fertilizer application cost by 1.10 to account for the cost of the investment (that is, 10% interest).

We computed profitability (US\$ ha^{-1}) for each fertilizer treatment and location as follows: we multiplied the difference in yield achieved by a treatment (for example, 50N–30P–30K) versus the control (0N–0P–0K) (kg ha^{-1}) by the maize price (US\$ kg^{-1}) and then subtracted the cost of the fertilizer (US\$ kg^{-1}) from that amount. For each location, we identified the maximum profitability that can be achieved, which of the 539 fertilizer treatments had the maximum profitability, and the yield and fertilizer use associated with that maximum profitability. Note that our measure of profitability is not inclusive of other costs associated with fertilizer use, such as labour.

Ecological and economic yield gaps. We computed the ecological yield gap as the difference between the attainable yield (that is, the water-limited yield, or the maximum yield that can be achieved without irrigation) computed with WOFOST and the reported current maize yields[27]. We computed the economic yield gap as the difference between the profit-maximizing yield and the current yield. Finally, we computed the relative yield gap to compare differences in the ecological and economic yield gaps for each location.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The experimental data compiled for the current study are available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/O9FYCV.

Code availability

The R code used is available at https://github.com/reagro/ecyldgap.

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Author contributions

C.B.-C., J.C. and R.J.H. conceived the research. C.B.-C. performed the data acquisition and processing. C.B.-C. and R.J.H. analysed the data. C.B.-C., J.C. and R.J.H. wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	We used the GARDIAN search engine to discover datasets and publications from repositories across the international agricultural research centers of CGIAR and others. Search keywords included Africa fertilizer, maize, fertilizer trials, nitrogen, macronutrient, soil fertility, and Nutrient Omission Trials. We compiled 227 datasets, that had 12,081 maize yield observations distributed in 1141 unique locations across SSA. We used a database of fertilizer prices in markets across 18 countries in SSA to predict the fertilizer price in these countries. We used a database of cereal prices across 168 markets and 30 countries in SSA.
Data analysis	We built a Random Forest model of maize yield in response to fertilizer applications and environmental conditions, using the R packages 'randomForest' and "terra" for the spatial data; we used WOFOST implemented in Rwofost; QUEFTS implemented in Rquefts. We predicted yield responses to 539 different combinations of nutrient applications for each of the 442,156 grid cells with maize. Nitrogen treatments were 0, and between 10 to 100 kg ha-1 in 6 steps of 15 kg ha-1, and from 100 to 200 kg ha-1 in four steps of 25 kg ha-1; Phosphorous and Potassium treatments were 0, and from 10 to 100 kg ha-1 by 15 kg ha-1. For each cell, we run both models 539 times. There were 44,156 cells with maize, thus we had a total of 373,013 x 539 x 2 = 476,644,168 runs. For urea prices, we fitted Random Forest models of urea prices as a function of longitude, latitude, and additional predictor variables that capture aspects of market access (distance to the nearest port; town with over 50,000 inhabitants; town with over 100,000 inhabitants; and town with over 250,000 inhabitants, demand (urban and rural population density and cropland and the environment (annual precipitation) . For maize prices, we fitted a random forest model and predict maize price at the beginning of the harvesting season as a function of access to market (travel time to market) and precipitation.

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The experimental data compiled for the current study are available at https://dataverse.harvard.edu/dataset .xhtml?persistentId=doi%3A10.7910%2FDVN%2FO9FYCV. , except where restrictions apply to the redistribution of these data, in which case we provide a link to the original source.

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Study description	We quantified the profitability of intensifying maize production across SSA with a mechanistic and an empirical machine learning model based on 12,081 trial observations that estimate local crop responses to fertilizer
Research sample	We used the GARDIAN search engine to discover datasets and publications from repositories across the international agricultural research centers of CGIAR and others. Search keywords included Africa fertilizer, maize, fertilizer trials, nitrogen, macronutrient, soil fertility, and Nutrient Omission Trials. We compiled 227 datasets, that had 12,081 maize yield observations distributed in 1141 unique locations across SSA. We used a database of fertilizer prices in markets across 18 countries in SSA to predict the fertilizer price in these countries. We used a database of cereal prices across 168 markets and 30 countries in SSA.
Sampling strategy	The search keywords used include Africa fertilizer, maize, fertilizer trials, nitrogen, macronutrient, soil fertility, and NOT.
Data collection	We used the GARDIAN (2020) search engine to discover datasets and publications from repositories across the international agricultural research centers of CGIAR and other providers. The search keywords used include Africa fertilizer, maize, fertilizer trials, nitrogen, macronutrient, soil fertility, and NOT. We compiled 227 datasets, that had 12,081 maize yield observations distributed in 1141 unique locations across SSA. We use a database of fertilizer prices in markets across 21 countries in SSA (30. Bonilla Cedrez, C., Chamberlin, J., Guo, Z. and Hijmans, R.J., 2020. Spatial variation in fertilizer prices in Sub-Saharan Africa. PloS ONE, 15(1), p.e0227764) to predict the fertilizer price in these countries. We use a database of cereal prices across 168 markets and 30 countries in SSA compiled by (Cedrez, C.B., Chamberlin, J. and Hijmans, R.J., 2020. Seasonal, annual, and spatial variation in cereal prices in Sub-Saharan Africa. Global Food Security, 26, p.100438.).
Timing and spatial scale	Sub-Saharan Africa
Data exclusions	n/a
Reproducibility	n/a
Randomization	n/a
Blinding	n/a

Did the study involve field work? ☐ Yes ☒ No

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