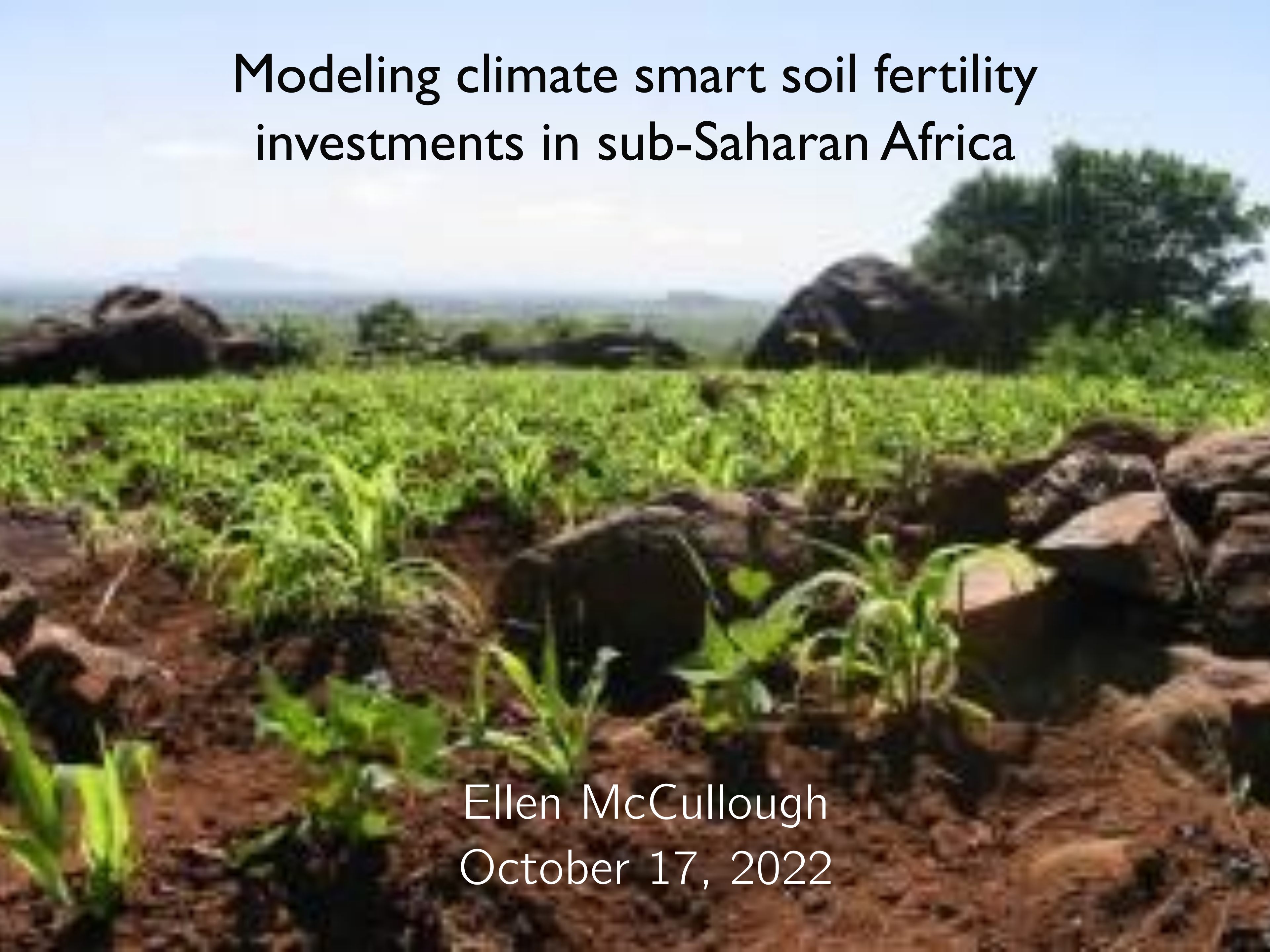
Modeling climate smart soil fertility investments in sub-Saharan Africa



Ellen McCullough

October 17, 2022

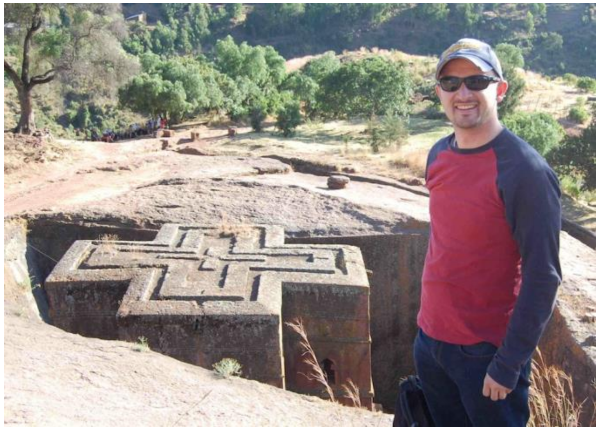
This is a paper 8 years in the making!

I started grad school at Cornell in 2011. In 2012, I entered an NSF Integrated Graduate Education and Research Traineeship (IGERT) on [Food Systems and Poverty Reduction].

In the summer of 2013, our cohort went to Ethiopia and spent two weeks with the Ethiopian Agricultural Transformation Agency where we developed a research proposal. 8 years later, we finally published our study!

Ellen McCullough, AEM

Julianne Quinn, CEE



Andrew Simons, AEM

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Ellen McCullough, UGA

Julianne Quinn, UVA

Andrew Simons, Fordham

Motivation

The majority of people in developing countries live in rural areas, and most of them depend on agriculture for their livelihoods (IFAD, 2016).

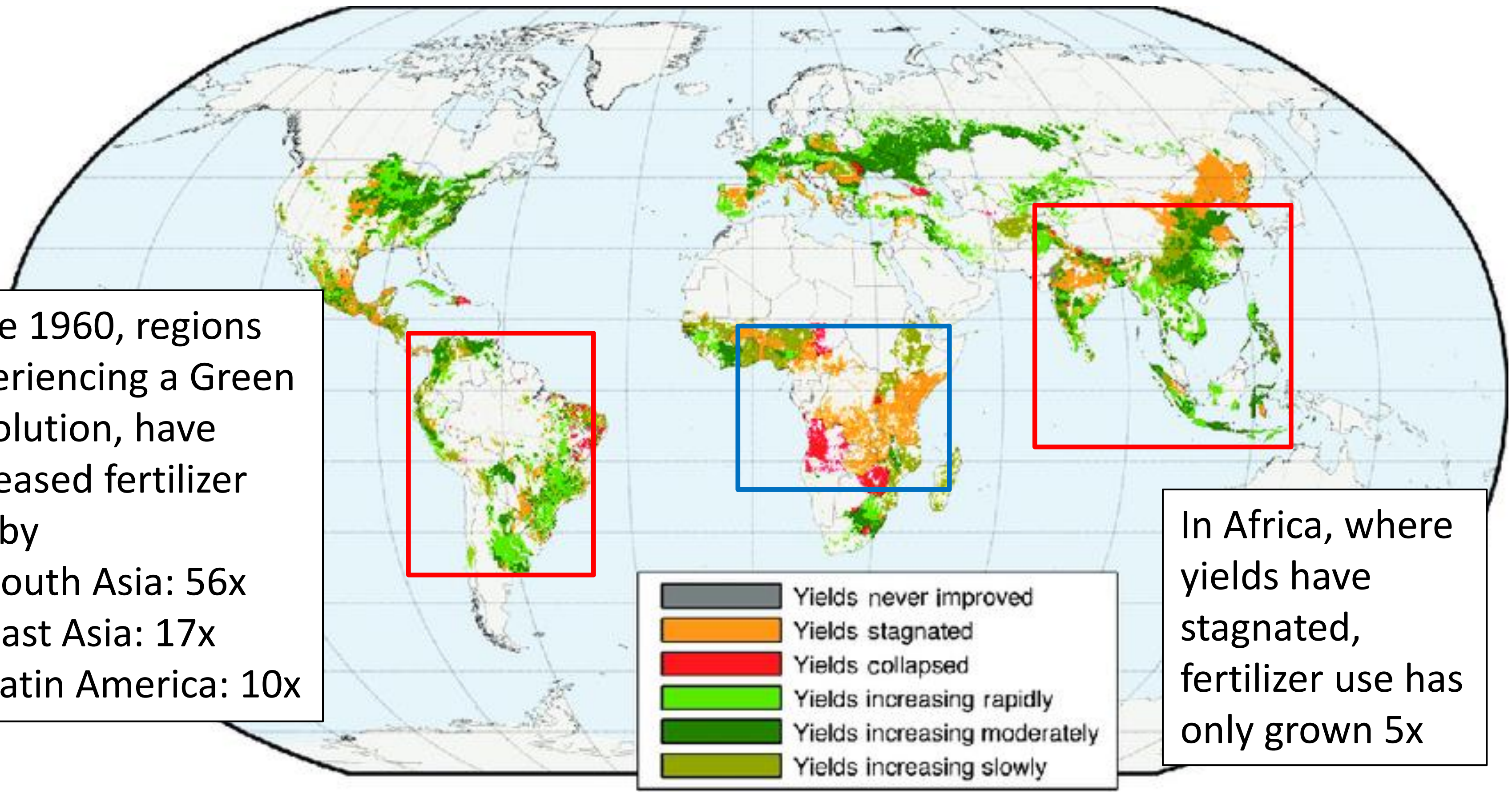
Food security for these smallholder farmers was greatly improved by the Green Revolution of the 1950s and 1960s.

Input intensification, of which fertilizer plays a key role, has accounted for 60% of agricultural output increases since 1960 in developing countries (Fuglie, 2018).

IFAD. (2016). Rural development report 2016: Fostering inclusive rural transformation.
Fuglie, K. O. (2018). Is agricultural productivity slowing?. *Global food security*, *17*, 73-83.

Motivation

But benefits of fertilizer have not been uniformly distributed



Since 1960, regions experiencing a Green Revolution, have increased fertilizer use by

- South Asia: 56x
- East Asia: 17x
- Latin America: 10x

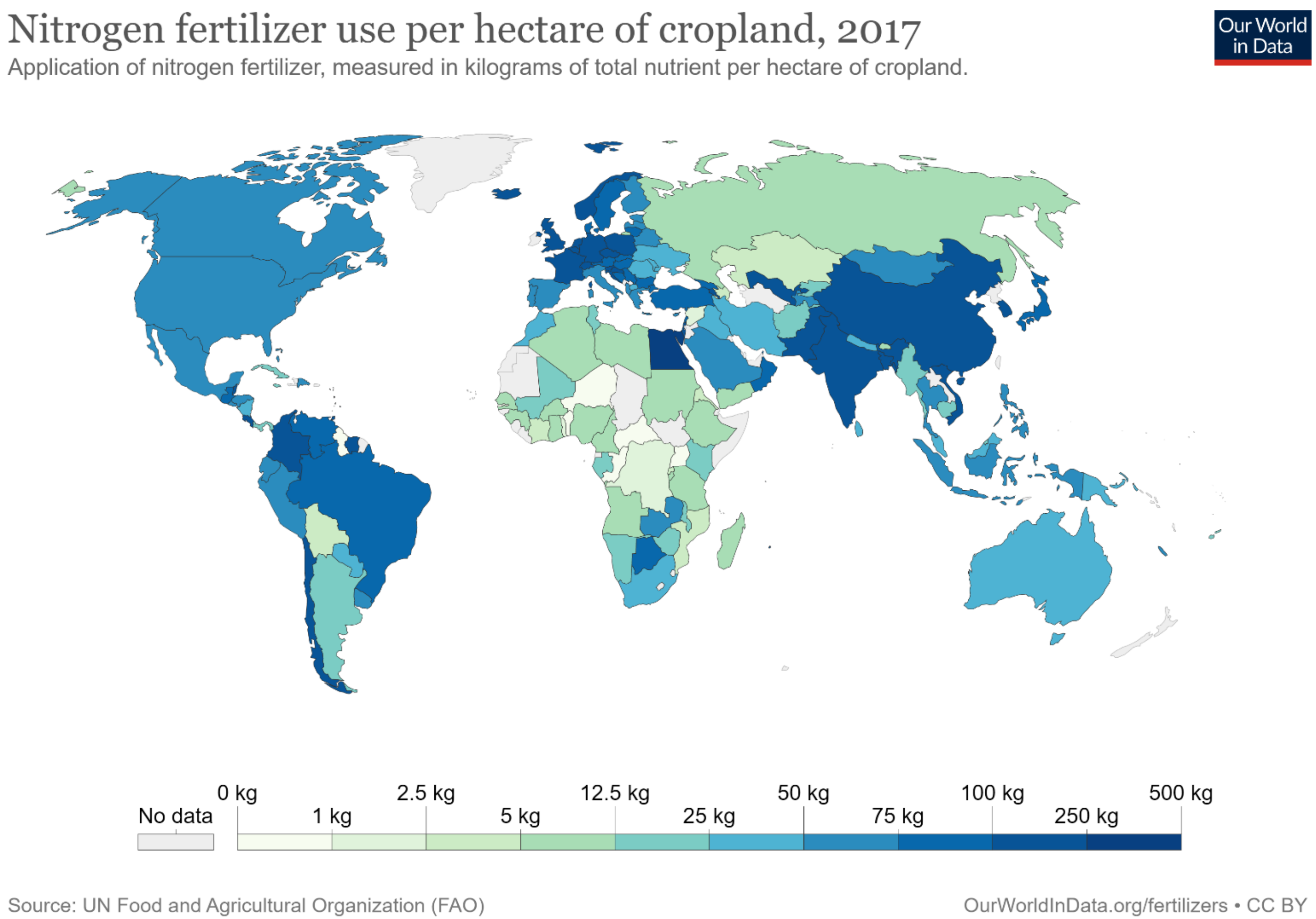
In Africa, where yields have stagnated, fertilizer use has only grown 5x

Smith, J. S., Gardner, C. A. C., & Costich, D. E. (2017). Ensuring the genetic diversity of maize and its wild relatives. *Achieving sustainable cultivation of maize*, *1*, 3-50.

Motivation

Low fertilizer adoption rates in Africa are not for lack of effort.

In recent decades, expenditures on fertilizer subsidy programs in the 10 largest African countries have accounted for 14-26% of their agricultural expenditures (Jayne et al., 2018).



Jayne, T. S., Mason, N. M., Burke, W. J., & Ariga, J. (2018). Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy*, *75*, 1-14.

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Research Questions and Hypotheses

Africa’s large scale trends raise questions:

- Why is fertilizer adoption so low in Africa?
- Could fertilizer subsidy programs be better targeted?
- Would other initiatives be more effective than subsidies?

Our hypothesis:

- Fertilizer adoption is low because using fertilizer is not profitable

We seek to:

1) understand variability of fertilizer use profitability from year to year and location to location
2) Inform targeting that could improve profitability

Mapping Soil Profitability in sub-Saharan Africa

We quantify the Internal Rate of Return (IRR) as:

$$IRR = \frac{\overset{?}{\boxed{p_y \Delta y}} - p_f \Delta f (1 + r)}{p_f \Delta f (1 + r)}$$

were

IRR need only exceed 0 for fertilizer to be profitable.

But farmers must decide whether or not to purchase fertilizer at the beginning of the growing season, before they know either their weather-dependent yield return, Δy, or the crop price at the end of the season, p_y.

Robust Profitability

Many studies assume farmers will adopt fertilizer if ***average*** IRR is above a target T (say IRR>30%).

We instead assume farmers will adopt fertilizer if they can expect an IRR > T *at least p% of the time* (say 70%).

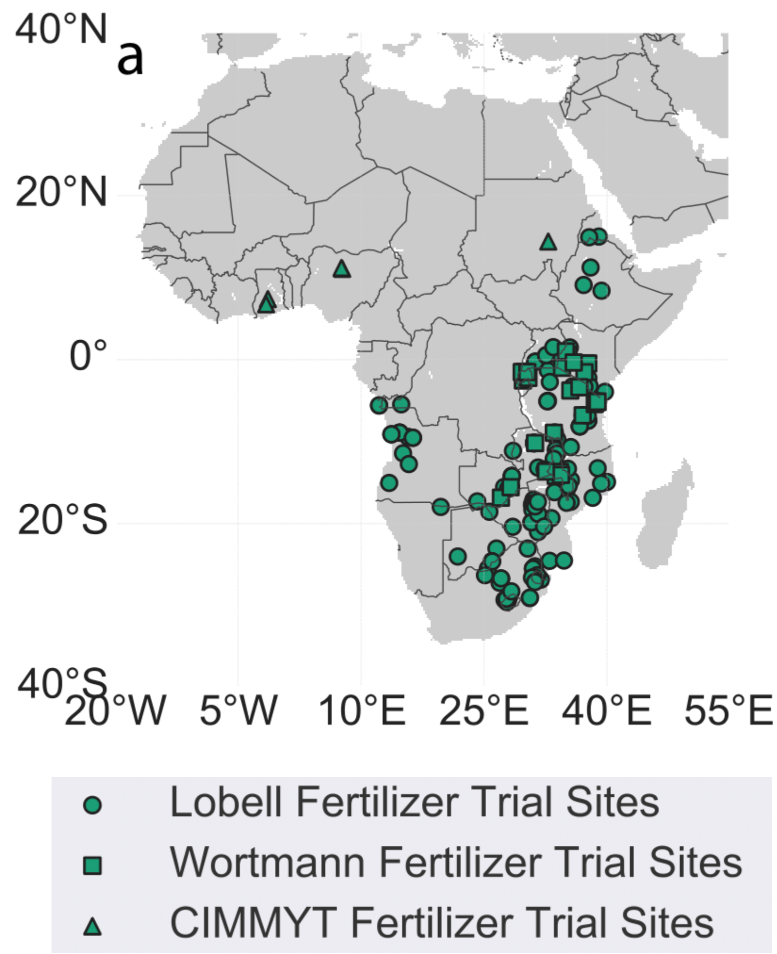
To estimate this throughout Africa, we need to understand:

1) The yield response to fertilizer adoption as a function of soil and weather conditions
2) Spatiotemporal soil, weather, and prices

Data to assess yield response to fertilizer: Maize trials

Several field studies throughout Africa between 1999-2007 and 2013-2016 have performed maize production trials in which no N management regime and an optimal-N management regime (120-125 kg/ha) were applied with 15-18 kg P/ha in both treatments.

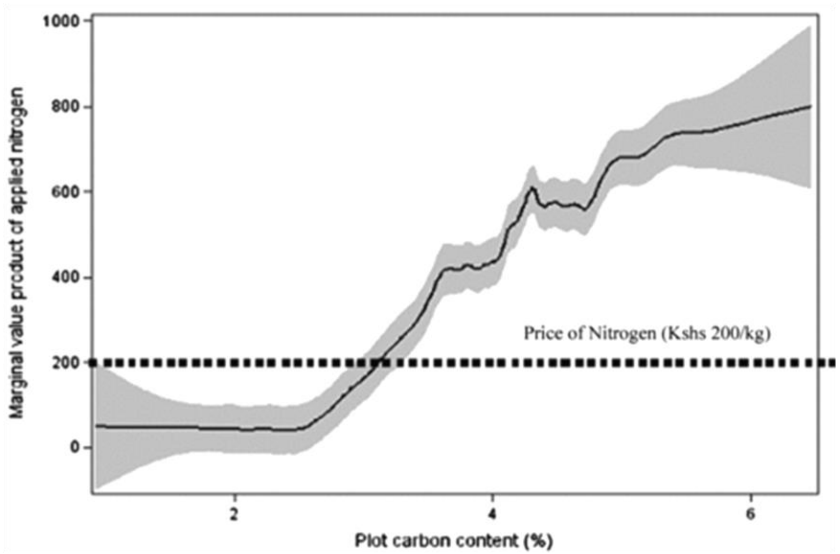
We use these datasets to estimate the maize yield return of applying optimal-N fertilizer.



Data to assess yield response to fertilizer: Soils

We expect the yield response to fertilizer to vary spatially and temporally based on soil and weather conditions.

For example, soil organic carbon (SOC) influences soil structure and retention of soil moisture and nutrients like N.



Marenya, P. P., & Barrett, C. B. (2009). State-conditional fertilizer yield response on western Kenyan farms. *American Journal of Agricultural Economics*, *91*(4), 991-1006.

Data to assess yield response to fertilizer: Soils

We expect the yield response to fertilizer to vary spatially and temporally based on soil and weather conditions.

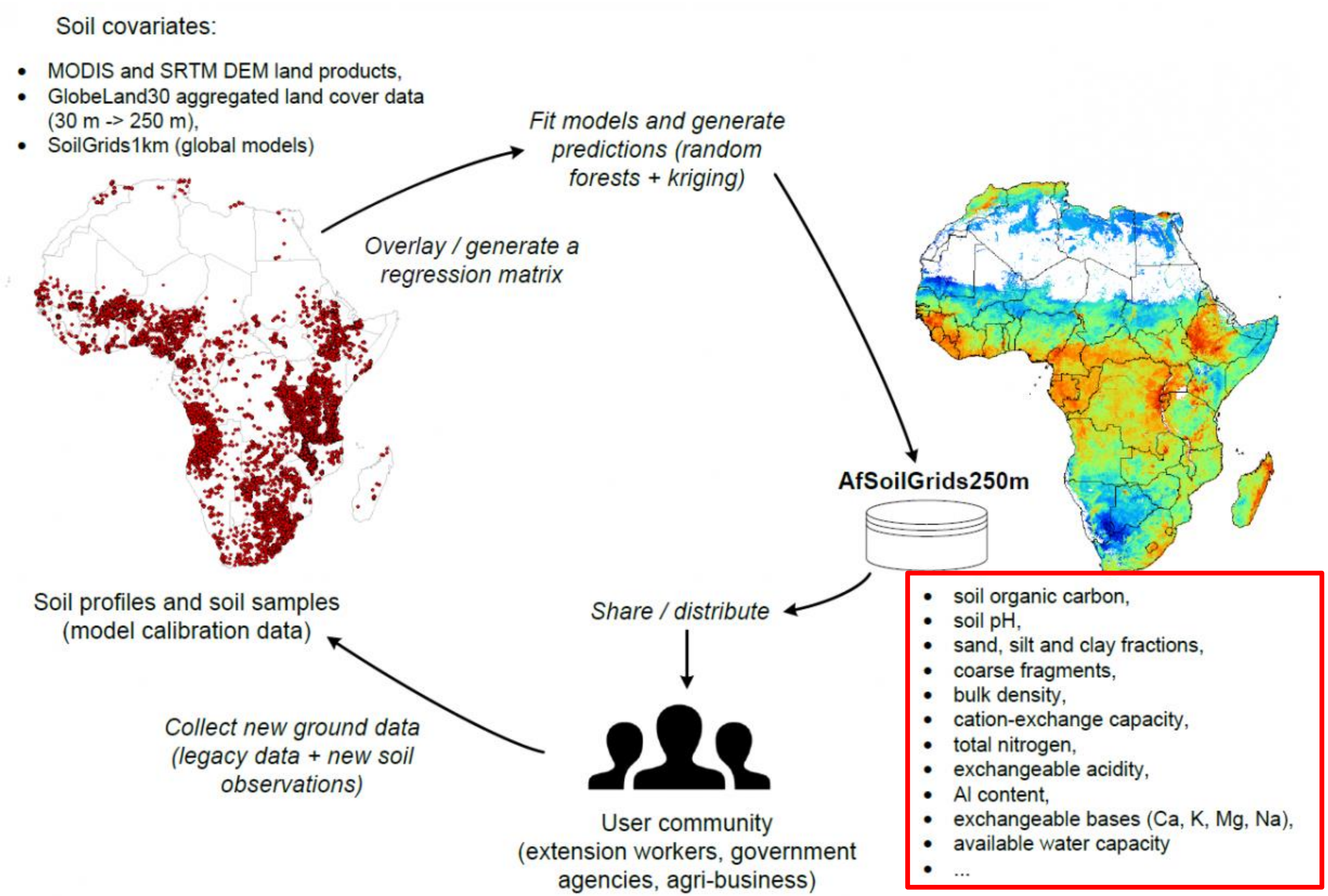
E.g., soil pH influences the ability of SOC and minerals to retain nutrients, with fertilizer-mineral interactions typically weakened as soils become more acidic (Sarkar and Wynjones, 1982).

In researcher-managed fertilizer trials in East Africa, fertilizer response was higher in clayey soils than sandy soils (Tully et al., 2016).

Sarkar, A. N., & Wynjones, R. G. (1982). Effect of rhizosphere pH on the availability and uptake of Fe, Mn and Zn. *Plant and Soil*, *66*(3), 361-372.

Tully, K. L., Hickman, J., McKenna, M., Neill, C., & Palm, C. A. (2016). Effects of fertilizer on inorganic soil N in East Africa maize systems: vertical distributions and temporal dynamics. *Ecological Applications*, *26*(6), 1907-1919.

Soil data at 250 m resolution from African Soil Information Service (AfSIS)



Data to assess yield response to fertilizer: Climate

Most farmland in sub-Saharan Africa is rainfed, and fertilizer response decreases with increasing water stress during the growing season (Haefele et al., 2006).

Negative relationships between temperature and African maize yields, but N application can mediate the effects of heat stress (Lobell et al., 2011).

We obtain precipitation and temperature data at 0.5-degree resolution from the European Centre for Medium-Range Weather Forecasts (ECMWF) between 1979-2018.

Haefele, S. M., Naklang, K., Harnpichitvitaya, D., Jearakongman, S., Skulkhu, E., Romyen, P., ... & Wade, L. J. (2006). Factors affecting rice yield and fertilizer response in rainfed lowlands of northeast Thailand. *Field crops research*, *98*(1), 39-51.

Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature climate change*, *1*(1), 42-45.

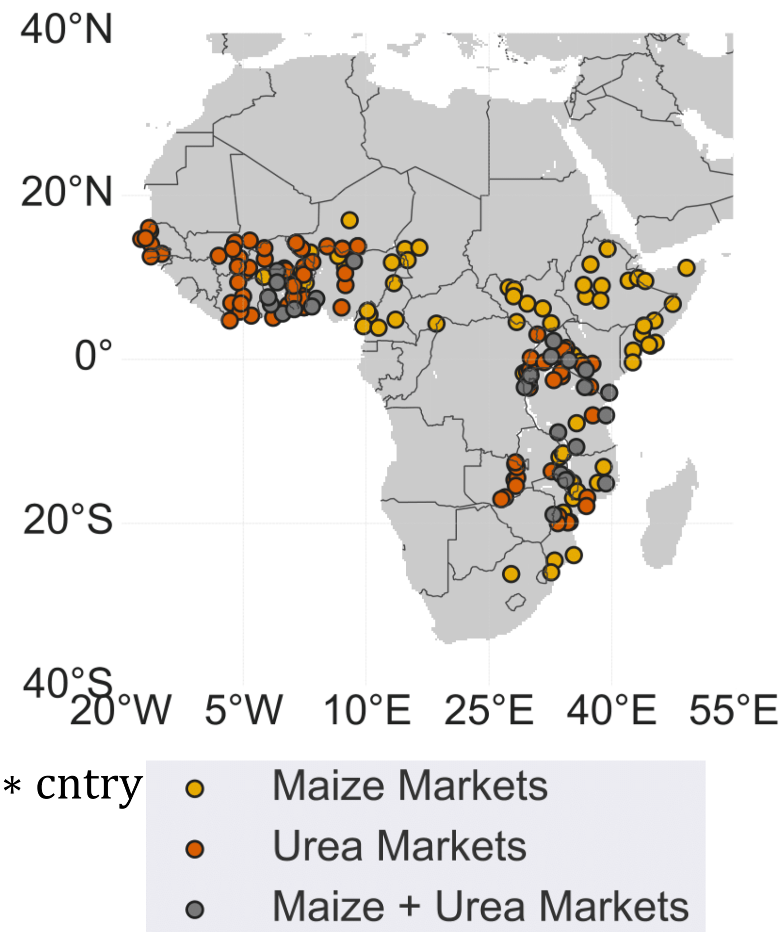
Data to assess profitability: Maize and urea prices

Maize and urea prices were obtained from the FAO Global Information and Early Warning System (GIEWS) dataset as far back as 2000, and urea prices from https://africafertilizer.org/local-prices/

We modeled prices at location *i* and time *t* (p_{it}) as a log-fraction of the world price at time *t* (p_{wt}) for maize (*m*) and urea (*u*) using a linear regression:

$$\ln\left(\frac{p_{it}^{m}}{p_{wt}^{m}}\right) = \boxed{\alpha_i^m} + \beta_1 \mathrm{mkt} + \beta_2 \mathrm{yr} + \beta_3 \mathrm{yr}^2 + \beta_4 \mathrm{mo} * \mathrm{cntry}$$

$$\ln\left(\frac{p_{it}^{u}}{p_{wt}^{u}}\right) = \boxed{\alpha_i^u} + \gamma_1 \mathrm{yr} + \gamma_2 \mathrm{yr}^2 + \gamma_3 \mathrm{mo} * \mathrm{cntry}$$



Location-dependent intercepts and their standard error were Kriged to interpolate prices outside market locations.

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Methods: Yield response to fertilizer

Estimation:

- Causal forest model to estimate the maize yield response to optimal-N using trial data
- Predictors: site-level soil characteristics and site-year level climate characteristics
- Not all trial sites used fertilizer exclusion – we balance with propensity weights
- We minimize the standard error on predictions in each site where the estimation does not use that site or year (avoid overfitting fertilizer response model to the data)

Validation

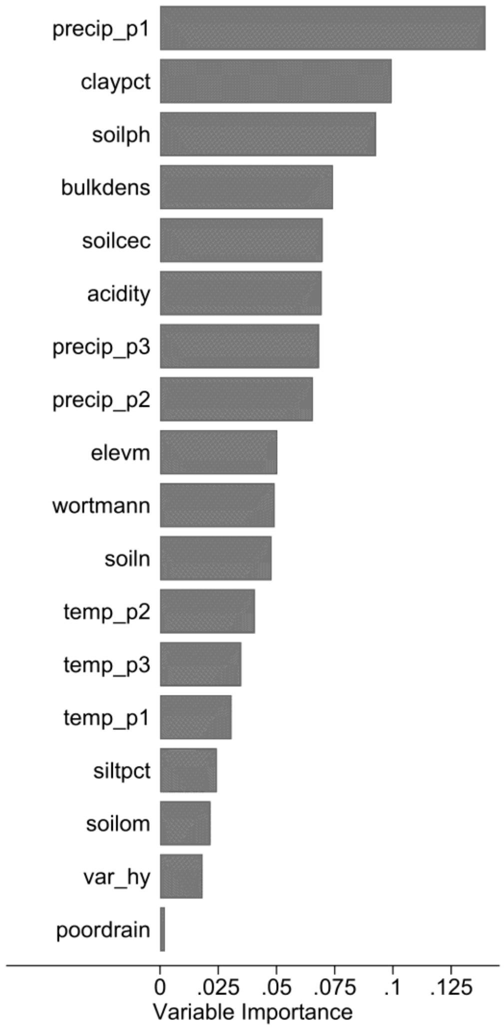
- Compare our out-of-sample yield predictions to those from a FGLS regression model (selecting variables stepwise from all main effects and interactions using 5-fold cross-validation)

Results: Yield response to fertilizer

	Causal Forest	Random Forest	FGLS
Ave predicted yield, F=0 (t/ha)		3.01	2.45
		(0.07)	(0.84)
Ave predicted yield, F=1 (t/ha)		4.27	4.51
		(0.18)	(0.70)
Predicted fertilizer response (t/ha)	1.49	1.26	2.07
	(0.13)	(0.12)	(0.52)
RMSE		2.26	5.20

Results: Yield response to fertilizer

Most important yield response predictor: precipitation in the first period of the growing season, followed by % clay and soil pH.



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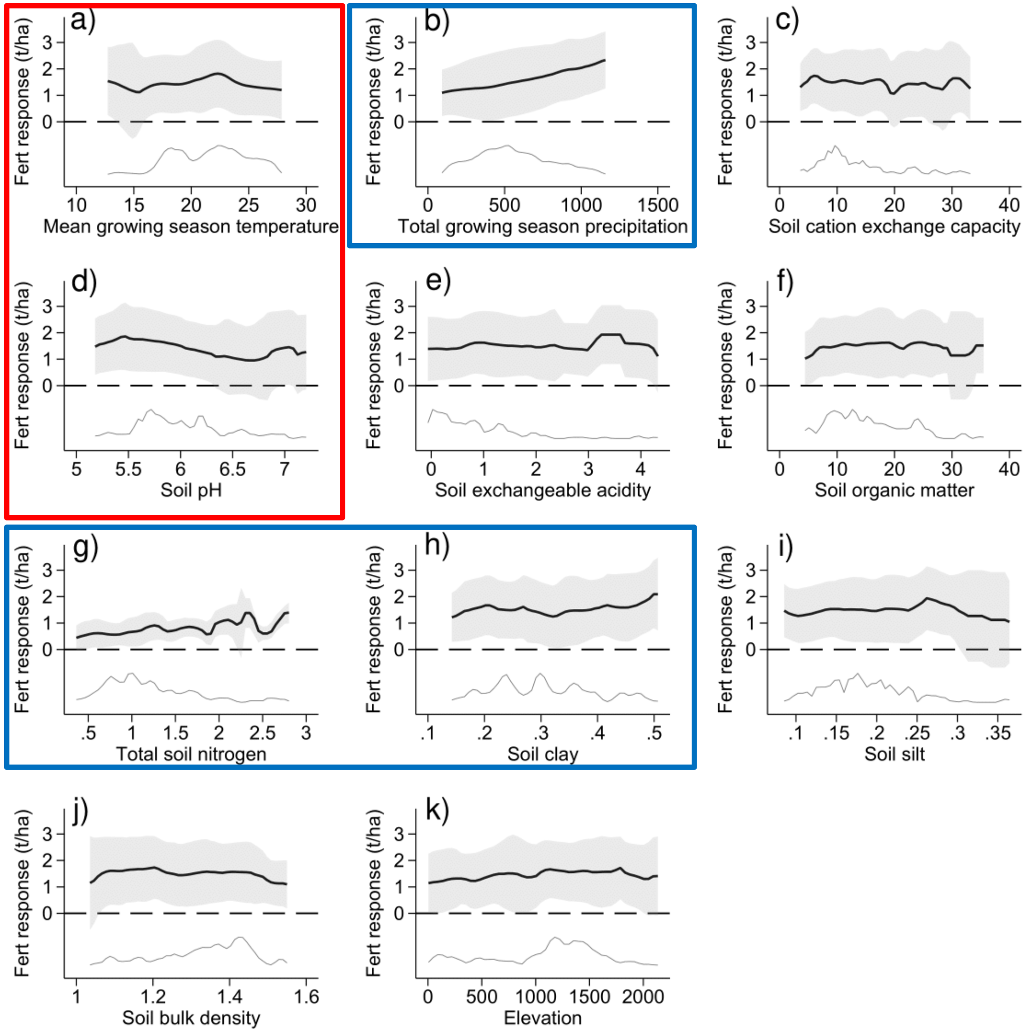
Results: Yield response to fertilizer

Fertilizer response exhibits a generally positive linear relationship with precipitation, soil N, and soil clay.

And an inverted U-shaped relationship with temperature and soil pH.

Other variables do not show strong relationships with the response, but may interact with other predictors.



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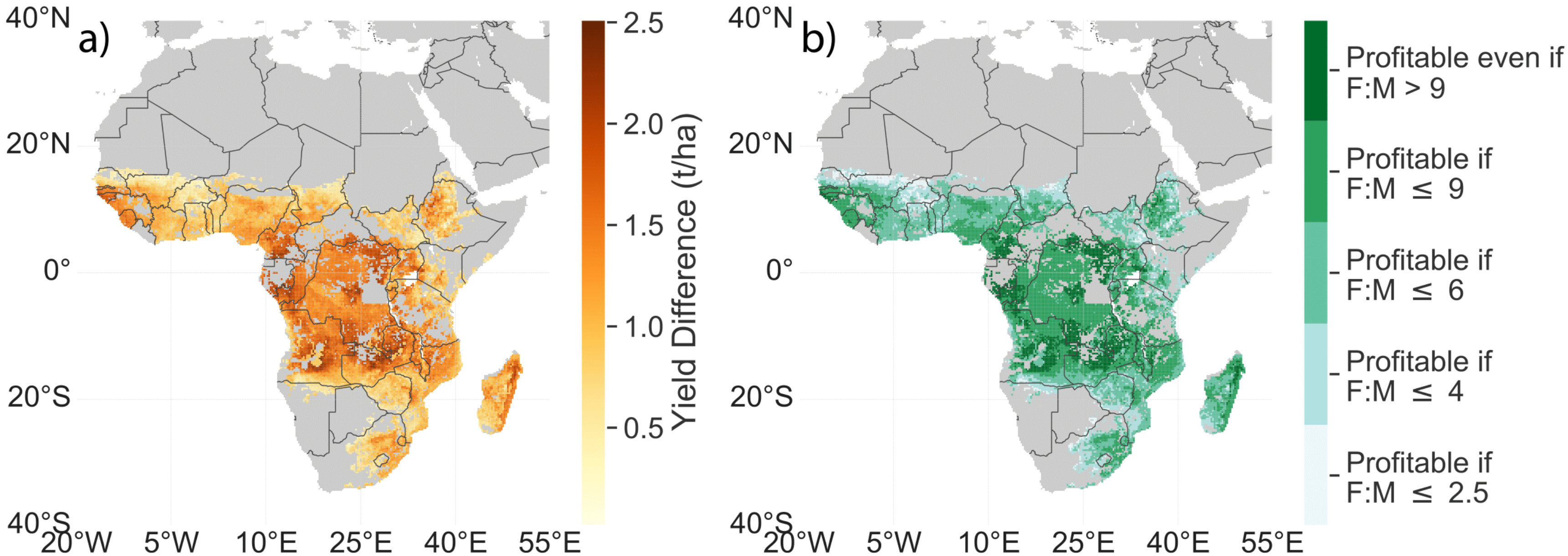
Fertilizer:maize price ratio required to meet profitability conditions



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Profitability distribution estimation

We estimate the profitability distribution at each site using a 1000-yr Monte Carlo simulation.

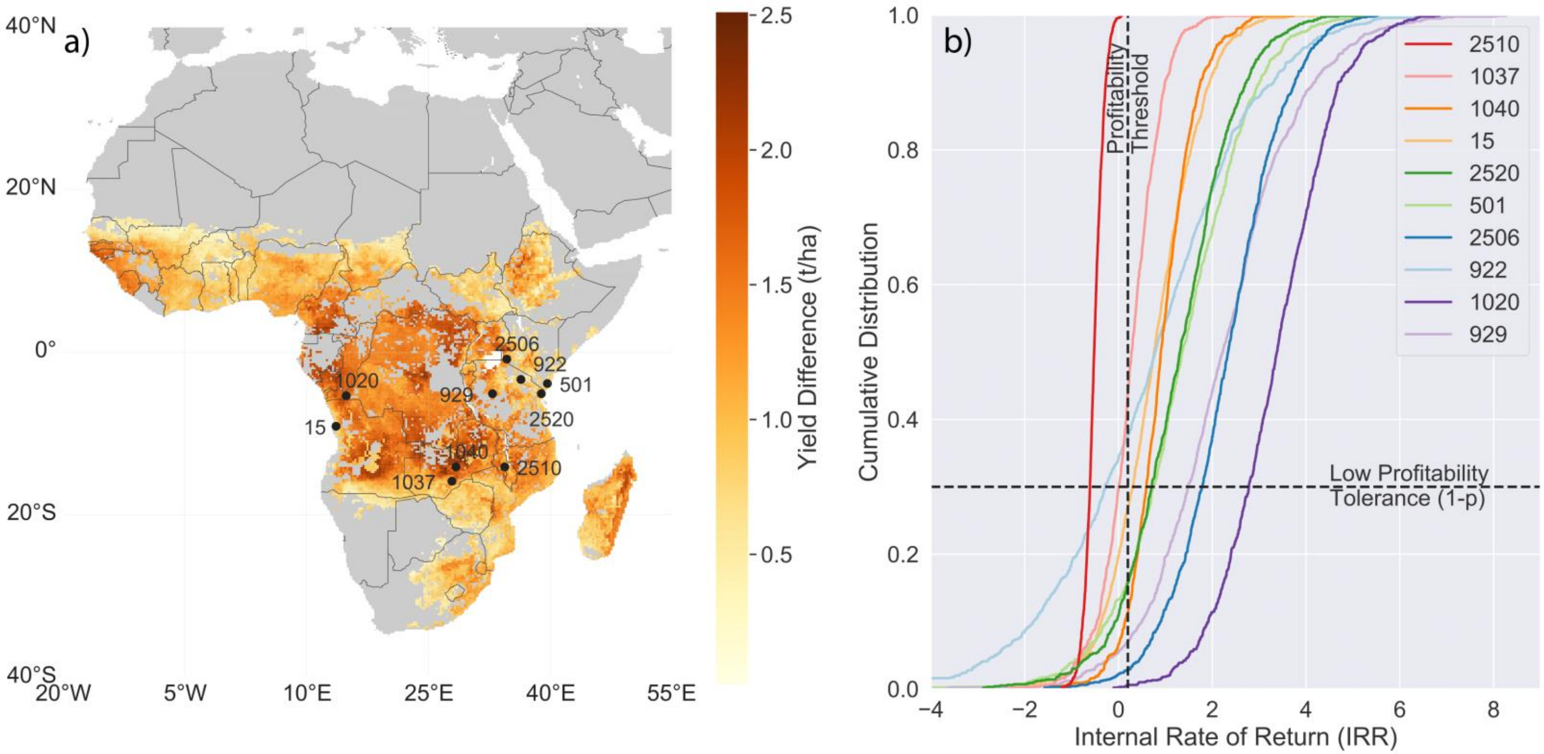
Generate a synthetic climate dataset (lag-1 autocorrelation) using historical data (1979-2018) and projecting linear trends.

Predict random errors in the yield response using standard error of the out-of-sample casual forest prediction

Predict random errors in output prices from a normal distribution with mean α and standard deviation $s(\alpha)$.

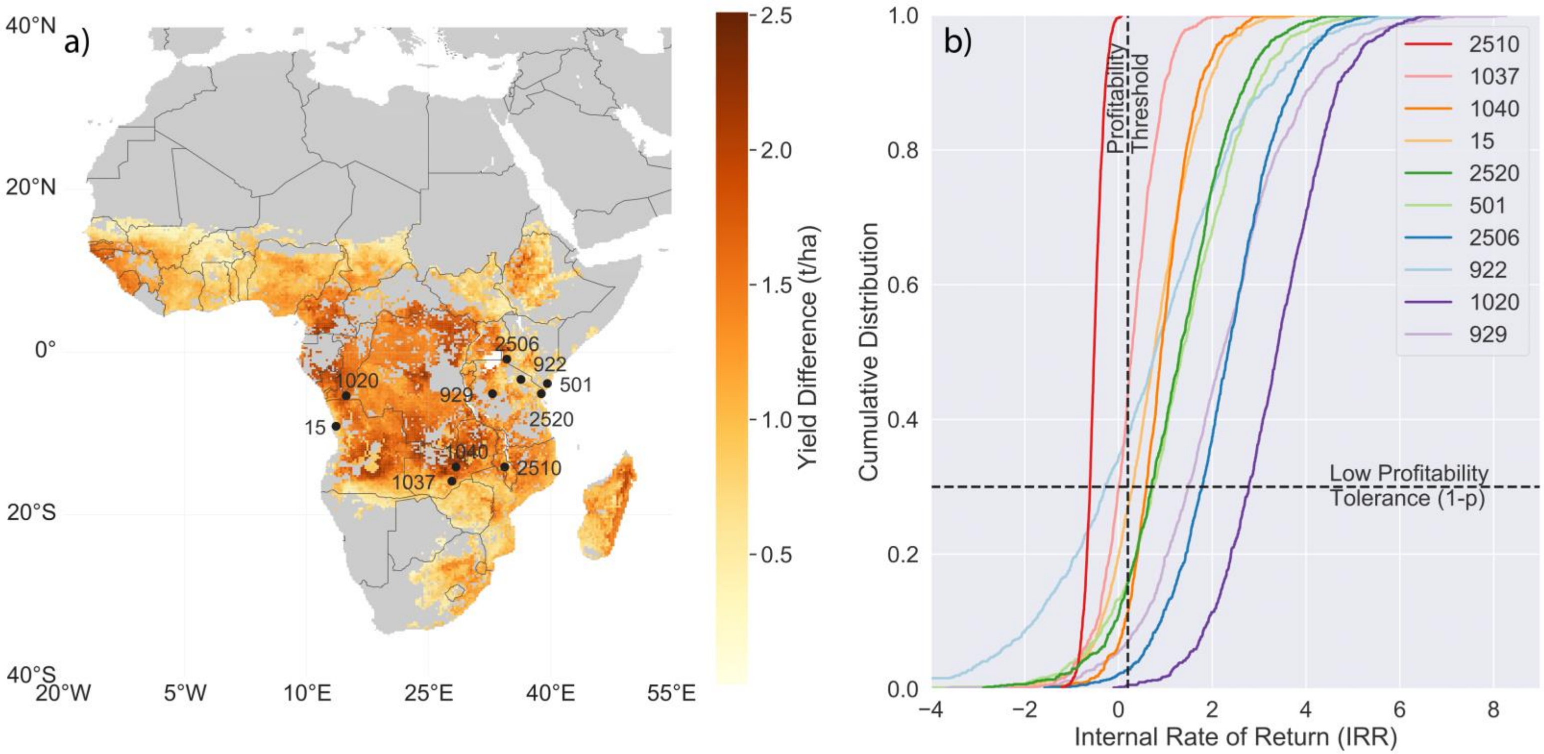
Profitability findings

The average yield response to fertilizer exhibits great spatial variation (a), and the profitability of that return exhibits differential temporal variability across sites (b).



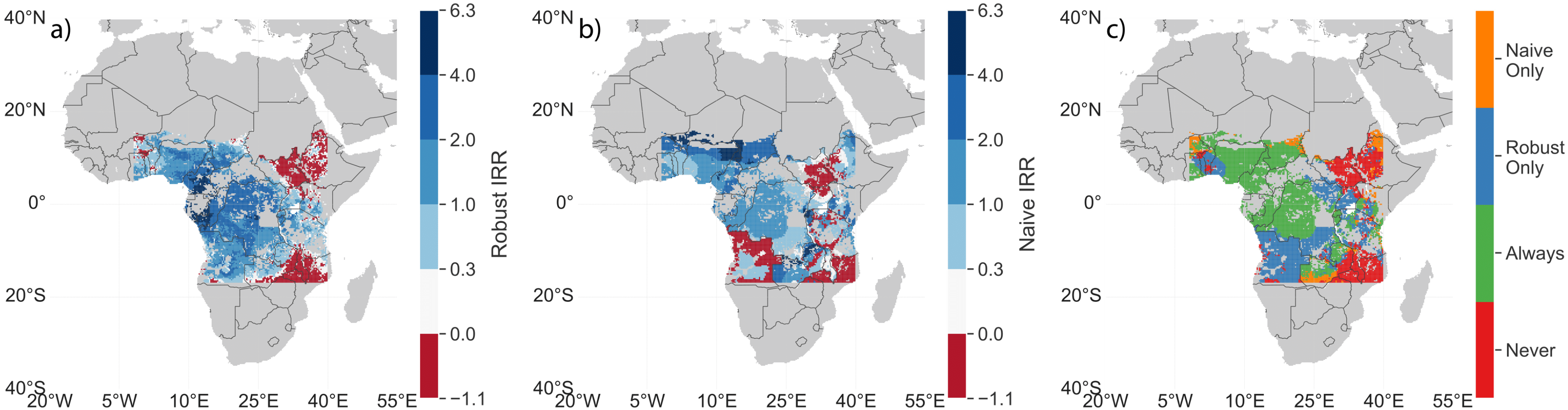
Profitability findings

Using a definition for "robust profitability" of IRR>0.3 in at least 70% of simulations, 3 of 10 randomly selected maize trial sites fail to meet this threshold (2510, 922, 1037).



Profitability findings

How does this definition of being "robustly profitable" $(\mathrm{P}(IRR > 0.3) > 0.7)$ compare with a "naïve" definition assuming profitability simply if $\mathbb{E}[IRR] > 0.3$?



Using a naïve profitability definition based on mean yield response to fertilizer classifies 12.5% of sites as profitable that our robust definition does not and vice versa.

Implications for targeting

We can use the previous map to target fertilizer promotion efforts where they are robustly profitable.

But why is profitability low in so may places?

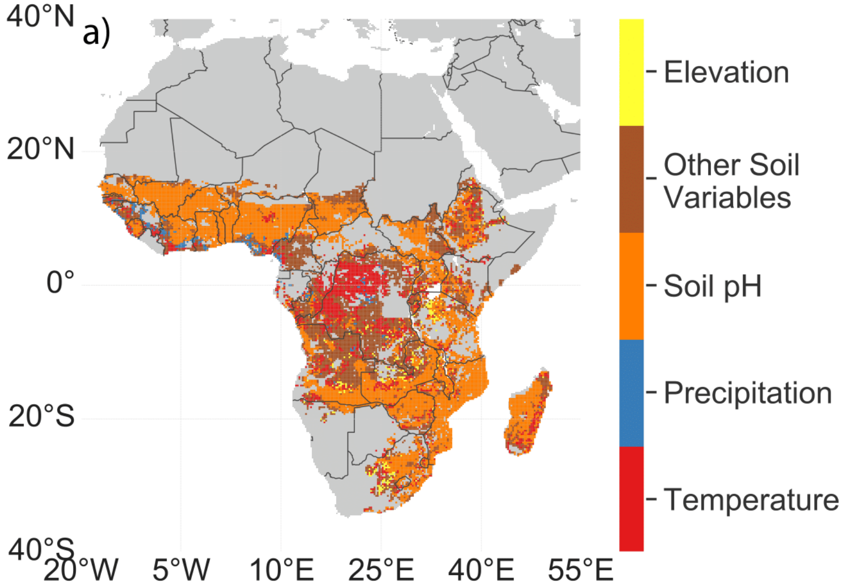
We perform a local, one-at-a-time sensitivity analysis perturbing each site's soil conditions and simulated weather and prices by +5% and -5%.

For each pixel, we find which variable elicits the greatest absolute change in yield response and IRR when it is perturbed.

Variable with greatest average effect across1000 Monte Carlo simulations

The variable to which most pixels' yield response is most sensitive is **soil pH** (51%), followed by **other soil characteristics** (31%), **temperature** (14%), **precipitation** (2%), and **elevation** (2%).

Precipitation is the most important predictor in the causal forest model, but explains more spatial variability than local temporal variability. Soil pH can be improved with interventions



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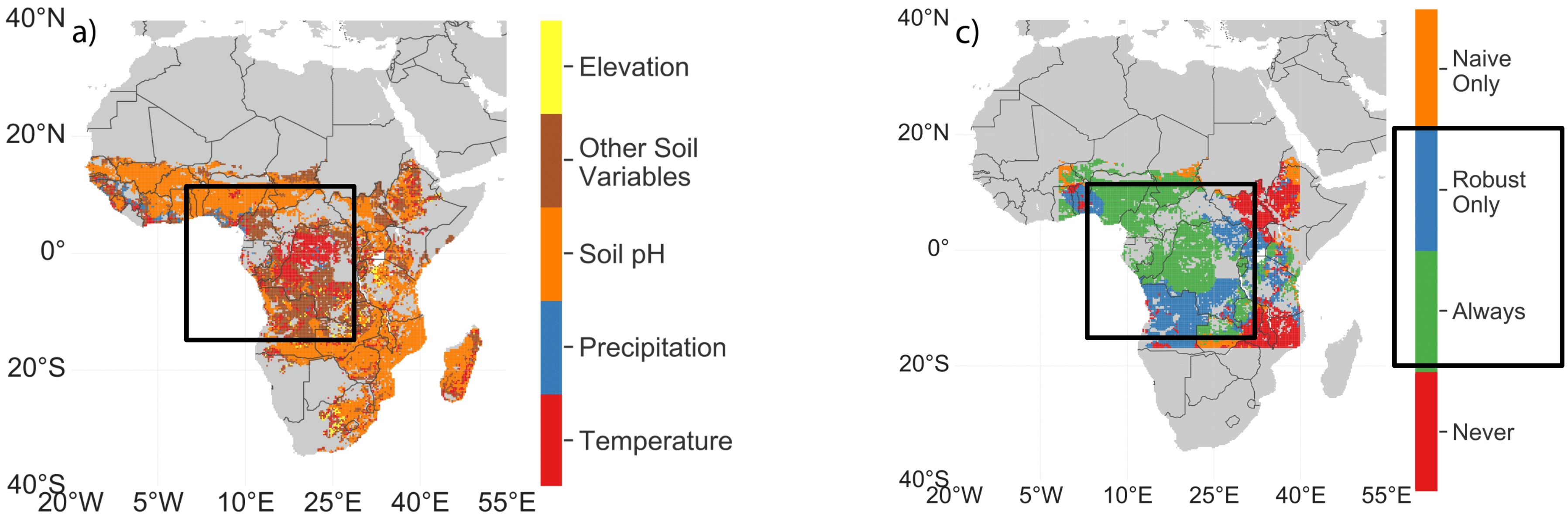
Variable with greatest average effect across 1000 Monte Carlo simulations

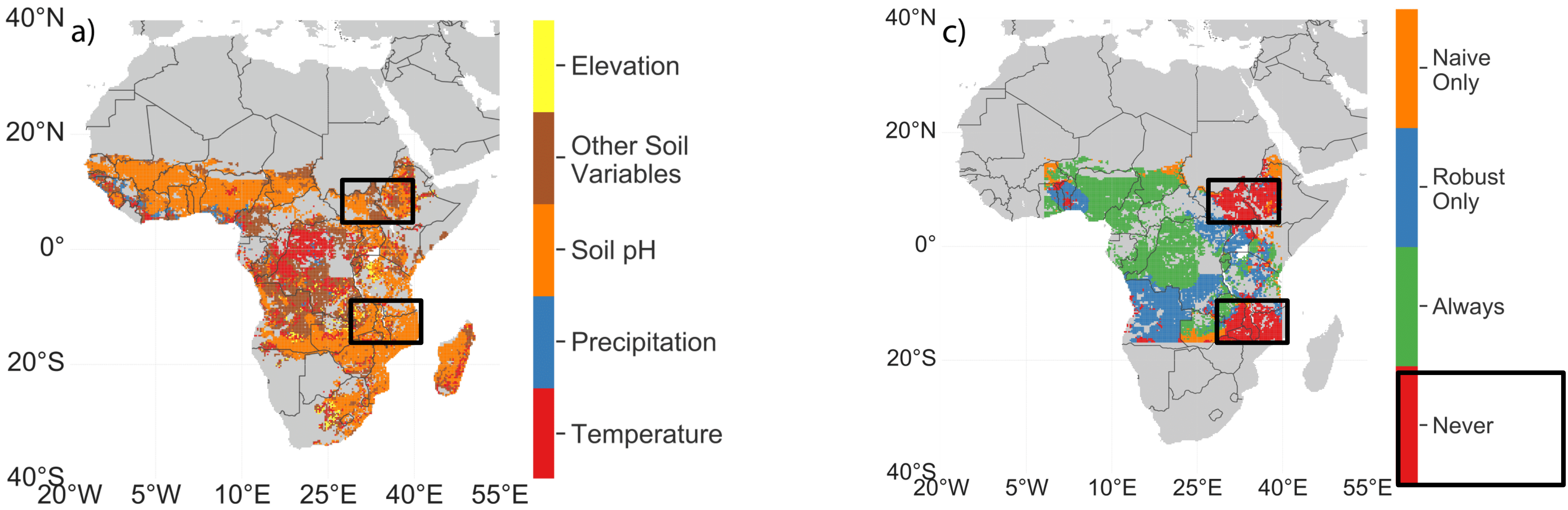
The robustly profitable locations are most influenced by temperature and other soil variables than pH.

The areas sensitive to temperature should be monitored, as their robust profitability may change in the future as temperatures continue to warm.



Variable with greatest average effect across 1000 Monte Carlo simulations

Locations that are never profitable are primarily sensitive to soil pH, suggesting soil amendments such as liming could make maize yields more responsive to fertilizer applications.



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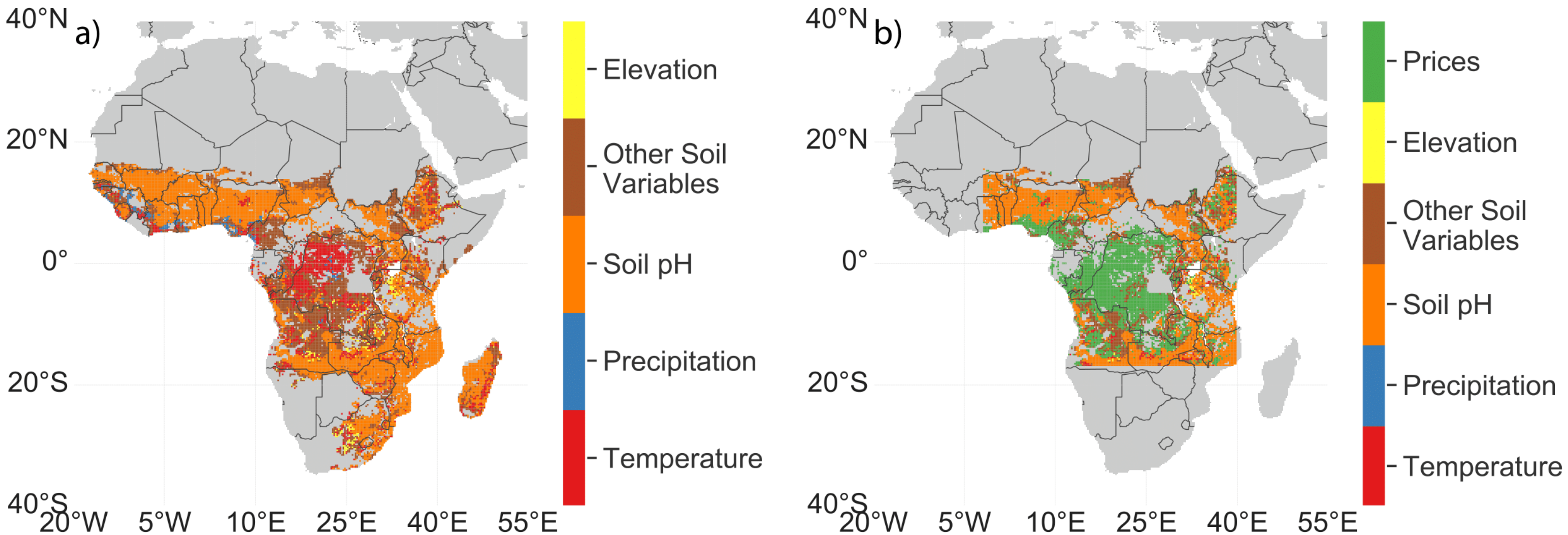
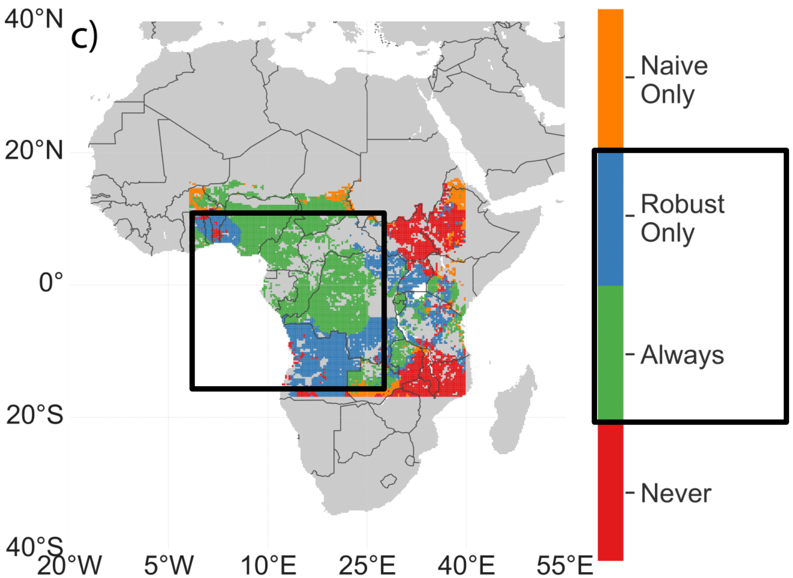
Variable with greatest average effect across 1000 Monte Carlo simulations

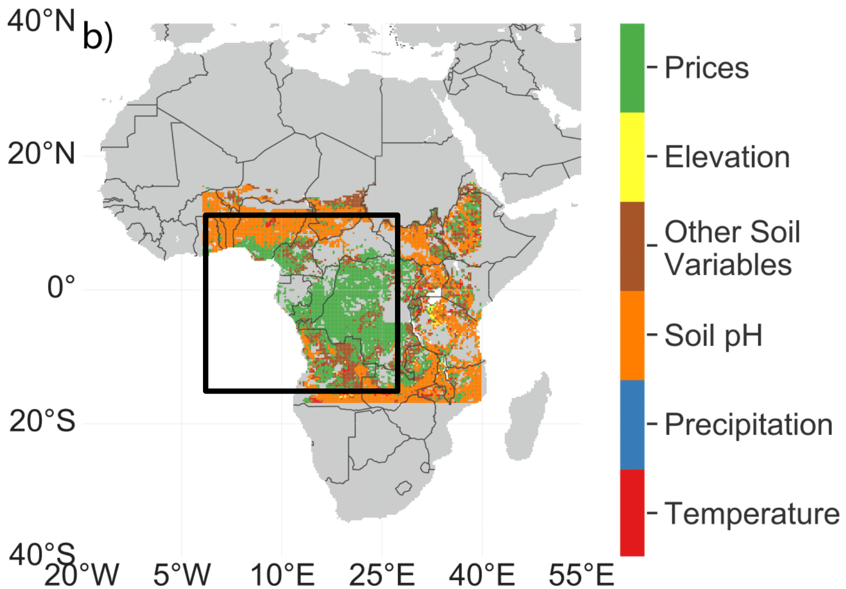
Moving to profitability, we see prices take over as the most dominant factor (40% of pixels), followed by soil pH (38%), other soil variables (19%), temperature (2%), elevation (1%) and precipitation (0%).



Variable with greatest average effect across 1000 Monte Carlo simulations

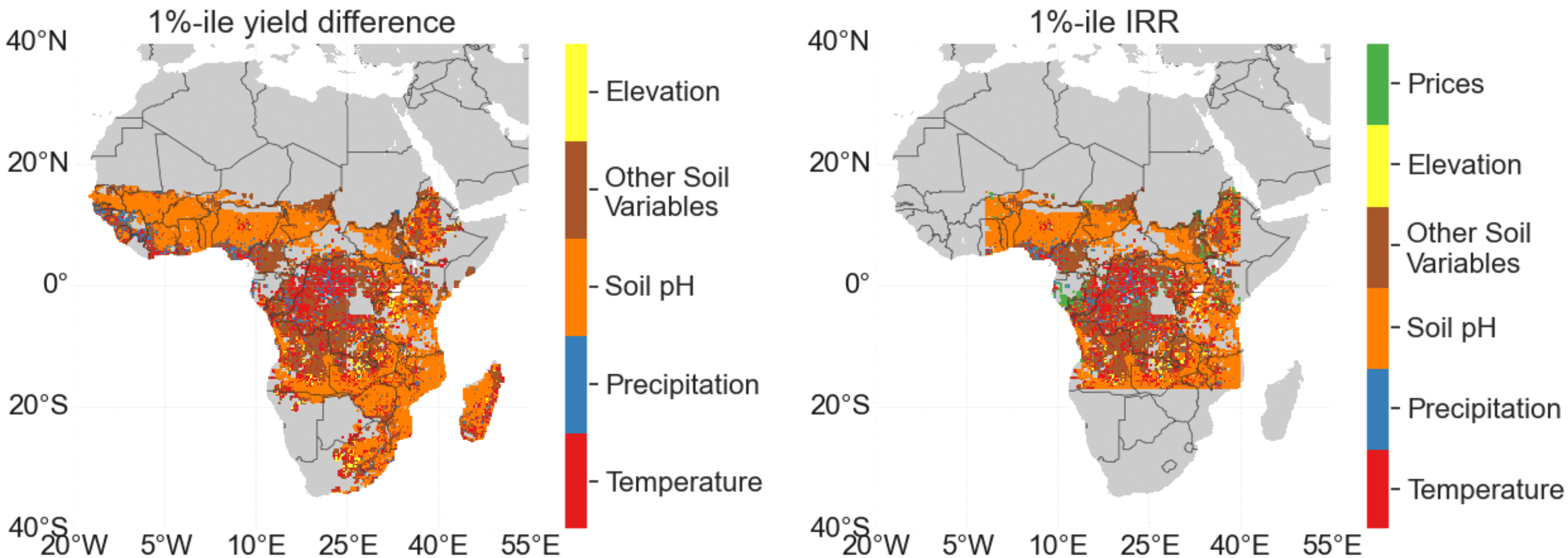
Prices are primarily dominant in the regions that are already profitable, but there a few locations in the never profitable region where prices overcome soil pH as most important, suggesting subsidies could be promising in conjunction with soil amendments there.





Variable with greatest effect in individual simulations

We can also see how this sensitivity changes across different simulated years, moving from low to high yield differences/IRRs.



The most important factor explaining the yield response does not change significantly across its distribution, but prices becomes more important as IRR increases, suggesting subsidies are less helpful in critical low IRR years.

Conclusions

It is important to understand uncertainty in yield response to fertilizer, and what variables are controlling it, to inform economic and soil health interventions.

Using a naïve profitability definition based on mean yield response to fertilizer classifies 12.5% of sites as profitable that our robust definition does not and vice versa.

Furthermore, we find price sensitivity is most prominent in areas that are already profitable, limiting the potential for subsidies to improve adoption.

But there could be great potential to improve adoption through targeted soil amendments.