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Farmers’ knowledge improves identification of drought impacts: A nationwide statistical analysis in Zambia

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HIGHLIGHTS

- The relationship between weather and agricultural output is changing over time.
- This may lead to biased climate impact estimates, especially in developing countries.
- Farmers’ experiential knowledge of climate impacts can add context to this problem.
- In a national survey of Zambia, farmers identified consistent patterns of pas shocks.
- Thus, farmers’ knowledge may be a more stable basis for impact estimates than yields.

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ABSTRACT

Climate adaptation policies rely on accurate estimates of weather-related impacts on community-level food insecurity. These estimates must capture local livelihoods and their varying sensitivity to climate extremes. This paper develops a novel methodology to address this need through incorporating farmer knowledge into robust drought impact assessments.

Using a new dataset of 925 farmer focus groups in Zambia, we investigate whether farmers’ recollection can identify consequential drought events more consistently than crop yields, which are conventionally used for this purpose. Zambia, like many countries, has experienced structural changes in its crop production systems over the last 30 years. Staple crop yields are therefore a weak proxy for food insecurity without wider socio-economic and agricultural context. We posit that in settings like this, farmers’ knowledge can provide the missing context for what constitutes a meaningful climate shock.

We conduct a statistical analysis of the dominant patterns of variability in farmers’ recollected drought years as compared to satellite rainfall. We find that farmers’ recall identifies meteorologically consistent patterns in shocks, going back 40 years. In contrast, conventional methods of regressing weather on maize yields to measure shocks would result in estimates that are biased and overconfident. Our analysis demonstrates, for the first time at a national scale, that farmers’ knowledge of climate shocks is a uniquely reliable source of impact data.

Practical implications

Climate adaptation policies that compensate farmers on the basis of observed or forecasted weather shocks are increasingly common. Such policies include parametric weather insurance, catastrophe bonds and forecast-based anticipatory action. In all cases, these policies rely on some quantitative “climate impact” formula which relates the measured weather in a given season and locality to the relative severity of livelihood shocks, and thus to the

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amount of financial resources disbursed to farmers in that area.

Drought insurance for farmers in Africa is a leading example of such a policy, having been initially piloted by NGOs and now adopted as national policy by the governments of Zambia and Ethiopia, among others. In the case of drought insurance, constructing a climate impact formula typically involves estimating the amount of staple crop yield per hectare farmers would expect to receive given a certain amount of rainfall. In doing so, practitioners make the implicit assumption that the relationship between weather, agricultural yields and community-level food insecurity is consistent over time and place, and can be inferred from past performance. However, our study contends that this is a very strong assumption that is likely to be violated in a number of consequential ways. In such settings, we posit that farmers' knowledge of historical climate events is a better source of information on impacts than yield data alone.

Zambia, where this study is set, is a typical case of the issues with the "status quo" approach to estimating climate impacts using yields. Agricultural policy in Zambia has changed dramatically over the last 30 years, as the government has introduced subsidized fertilizer for smallholder farmers via its Farmer Input Support Programme (FISP). This has led to dramatic changes in the structure of Zambian agriculture, with smallholder farmers – many now able to access fertilizer for the first time – leading a takeoff in agricultural growth. This structural shift means that the relationship between weather and agricultural production now is very different than it was 20 or even 10 years ago, as prior studies have noted. Zambia also has a diversity of agro-ecological production systems within its borders, each of which has different agricultural inputs and practices.

We argue that given the difficulty of modeling these diverse adaptation responses – which are typical of many places in the agrarian Global South – farmers' own recollection of the years in which they were impacted by weather can provide a better basis for measuring livelihood shocks than administrative data, like crop yields, could alone. Farmer knowledge is significant not only because of the paucity of historical yield data, but also because of the importance of knowledge co-generation and representing farmer perspectives in official decision-making. At the same time, farmers' surveyed recall of historical events may be subject to cognitive biases or under-representation of marginalized perspectives, so it is important to test its coherence and reliability systematically, which most past studies have lacked the data to do.

Farming communities tend to have strong memories of the years in which the community had notably "good" or "bad" harvests. Thus, communities can often reliably identify which years were relatively worst in terms of a qualitative ranking, which is the methodology employed here. This knowledge embodies aspects of the local climatology, cropping practices used, expected production and community needs – context which administrative data or models alone cannot provide. In Zambia, the government has collected this kind of focus group data on ranked drought years from a nationally representative survey of nearly 1,000 villages across the country, which we use as the basis for this study.

We hypothesize that if farmers' knowledge is a reliable source of data on drought shocks, it will exhibit patterns of variation over time and space that are both internally coherent and consistent with the patterns of variation in rainfall deficit that we can observe. We further hypothesize that if the relationship between weather and agricultural yields is changing over time due to adaptation policy, then the typical approach to estimating weather shocks to livelihoods via the proxy of yields will only be consistent over a short time span (in which agricultural practices can be held constant), and will be biased and / or overconfident over a longer time horizon.

In the first part of the study, we investigate how farmers' recollected worst drought years in Zambia compare to the weather record across time – i.e., which years had the worst droughts – and place – i.e., which locations tend to experience drought around the same time. We find that farmers' recollections of drought are strongly consistent with rainfall deficits over both space and time, as measured against an index of meteorological drought which is similar to the one the Government of Zambia uses for insurance. We use the government of Zambia's official drought insurance index as our measure of weather, as it represents local decision-makers' judgement on which aspects of weather (times of the season, etc.) should be prioritized financially.

We also compare farmers' recollected worst drought years against historical data on estimated maize production. We find that farmers' top recollected drought years are associated with a drought-induced disruption from the typical yield in that time and place, even as the absolute *amount* of yield associated with farmers' worst years varies. However, since the historical record of yields is relatively short (~20 years) and missing for some years, we are limited in the systematic conclusions we can draw from this comparison.

In the second part of the study, we estimate the bias that might arise from ignoring farmer knowledge and instead using a "status quo" approach to estimating climate impacts through the direct relationship of weather to yield. We find that such an approach, typical of prior work, would be biased over time, leading to overestimates of drought impact in more recent years and underestimates of drought impact in the more distant past. Including controls for agricultural policy mitigates this bias, but also limits the generalizability of the estimates, underlining how yields are only a meaningful proxy for climate impacts in a narrow spatio-temporal context.

Taken together, these findings have strong and actionable implications for the practice of climate services. First, we find that farmers' experiential knowledge is a strong proxy for weather shocks to livelihoods, across a wide variety of spatial and temporal contexts. Second, we find that assuming constancy in the relationship between weather, yield and livelihoods, as agricultural climate impact studies have typically done, would lead to inaccurate and overconfident conclusions. These shortcomings could be avoided, or at least mitigated, by starting from farmers' own experience as the basis for estimating climate impacts. For example, while farmers' self-reported impacts cannot be used directly to determine index insurance payouts, they could be used to tune a model of drought impacts to better reflect local context. The methodology for collecting this kind of historical climate impact data is increasingly standardized and can be applied at scale, as the Government of Zambia did. Future work could explore this kind of community-based climate impact assessment in other settings, including how it could be used to optimize a model of drought severity for policies like parametric insurance and forecast-based anticipatory action.

1. Introduction

1.1. Motivation

Climate adaptation policies rely on quantitative estimates of weather-related impacts on community-level food insecurity. Parametric drought insurance, forecast-based anticipatory action, and catastrophe bonds are just a few examples of policies that use impact data to relate weather severity to a financial decision, or to evaluate the adequacy of a decision rule retrospectively. However, there is never a single source of "ground-truth" data on impacts. Decision-makers must instead rely on a variety of proxy data sources that are associated with different aspects of impact. Staple crop yield is a common proxy for the impacts of drought, particularly in Africa, where rain-fed smallholder agriculture predominates (Lobell et al., 2011). Survey data on farmers' self-reported climate impacts is another (Enenkel et al., 2020; Osgood et al., 2018). Both sources of data have potential biases and practical limitations, and the choice of which to use has significant implications for decision-making. However, no prior work has systematically compared which type of data is a more reliable basis for measuring drought. This paper does so, taking advantage of a novel, nationally representative dataset of farmer focus groups in Zambia.

Yield data is readily available in most countries and distills agricultural livelihood down to a single number. However, its use as a proxy for drought shocks may be confounded by a number of factors. First, the non-weather factors of agricultural production – input use, farm structure, planting practices, crop varieties, and so on – vary greatly over time and space due to changes in government policy and communities' adaptation practices. For this reason, decision rules which rely on the empirical relationship between drought and yield to approximate shocks to livelihood, without accounting for context, may lead to biased or inaccurate choices of when and where to allocate assistance. In statistical terms, the relationship between yields and weather over time may exhibit bias from spurious trends and / or imprecision from serial correlation that cannot be easily modeled (Wooldridge, 2002). Second, this issue is exacerbated by the limited availability of yield data in the Global South – the historical record from administrative data is typically short and may contain gaps and inconsistencies (Tenorio et al., 2024). Third, the relationship between agricultural production and household livelihoods depends on farmers' place in the food system – a given amount of yield does not mean the same thing to a large-scale commercial farmer and a smallholder subsistence farmer.

Given these challenges, farmers' experiential knowledge of shocks may provide more relevant information on livelihood impacts than administrative data alone (Rodrigues and Shepherd, 2022). Previous work in the region has shown that in surveys, farmers tend to reliably recall specific instances in which weather shocks disrupted their expected crop output (Dorward et al., 2020; Osbahr et al., 2011; Young et al., 2021). Farmers' event-based knowledge has shown utility in applications like ground-truthing weather index insurance (Enenkel et al., 2020; Osgood et al., 2018). However, farmers' accurate knowledge of events does not necessarily translate to accurate knowledge about summary statistics like the long-term average or trend in weather (Moyo et al., 2012). Relatedly, studies have observed that recall-based data is subject to cognitive biases like recency bias and telescoping, and may be driven by the political and social salience of specific events (Beegle et al., 2012). There is thus a need for more systematic investigation of the relationship between farmers' recall and weather shocks.

This paper speaks to this growing literature on climate impact metrics by studying farmers' perceptions of historical climate events on a nationally comprehensive scale. We wish to understand whether there is a statistically identifiable signature of major rainfall deficits in farmers' perceptions of their worst drought years. If so, then farmers' experiential knowledge could be a reliable basis for measuring livelihood shocks in spatio-temporal context, particularly where other sources of ground-truth data are unavailable.

By way of contrast, we also wish to understand whether there is probable bias or overconfidence in estimates of weather impact on yields due to un-modeled adaptation policy. If so, then the typical approach to estimating weather shocks to livelihoods via the proxy of yields will only be valid over a short time span (in which agricultural practices can be held constant), and will be inconsistent and / or inefficient over a longer time horizon.

To answer these questions, we take advantage of a novel survey dataset on farmers' recollected worst drought years sampled from nearly 1,000 villages across a nationally representative cross-section of Zambia. As detailed in **Section 1.3**, Zambia is an ideal case for studying the problems of heterogenous weather impacts and adaptation: while much of the country faces risk from drought, there is a diversity of agro-ecological zones within its borders, each of which has different climatology, agricultural factors of production and typical cropping practices. Zambia has also experienced large-scale changes in national agricultural policy over time, including the introduction of subsidized fertilizer for smallholder farmers.

Previous work has lacked the data to study how these large-scale variations relate to community-level impacts. We address this gap through the use of a novel, large-scale (n = 925 villages) and geographically representative government survey dataset, which allows us to rigorously analyze how patterns in farmers' recollected drought years relate to patterns of climate shocks. Then, we compare these findings against estimates of drought impact based on yield alone, in order to understand whether farmers' knowledge can provide a better contextual basis for measuring and evaluating weather shocks.

1.2. Literature review

Across timescales – near-term insurance policy evaluation, medium-term forecast-based anticipatory action, and long-term climate change impact studies – and disciplines – economics, agronomy, meteorology – a great deal of established work has relied on linear regression-based estimates of the effect of temperature and / or precipitation on crop yield as a proxy for weather's impact on community food insecurity (Benami et al., 2021; Carleton and Hsiang, 2016; Lobell et al., 2011). Subsequent work has pointed out that these estimates are often biased over time and place due to confounding trends in the factors of production (Mukherjee et al, 2018) or other time-dependent factors (Lemoine, 2018; Mérel et al., 2024), and that they fail to capture the dynamic aspects of climate adaptation (Haasnoot et al., 2020). These omissions can lead to estimates that are biased due to spurious trends and / or inefficient due to serial correlation (Wooldridge, 2002). Case studies of parametric policies like weather index insurance have related these modeling shortcomings to farmers' frequent mistrust of these policies when put into practice (Lobell et al., 2020; Michler et al., 2021; Michler et al., 2022).

Climate impact estimates that attempt to account for adaptation have typically done so through the inclusion of a time trend or interaction term in the impact regression estimation (e.g. Hultgren et al., 2022); however, these approaches do not account for non-linearities, like the sudden introduction of a new agricultural policy (Benso et al., 2023), and the choice of functional form is typically arbitrary, lacking a principled basis (Bearpark and Palomba, in review). Direct modeling of the non-weather factors of production (e.g. fertilizer use, seed variety, soil type, etc.) in climate impact estimates has been limited due to a lack of comprehensive data on such factors – particularly in the Global South (Myeni et al., 2019) – and the assumptions imposed by crop models, which introduce significant model uncertainty (Rosenzweig et al., 2014). Machine learning approaches to impact estimation also struggle in these settings, due again to the sparseness of data, as well as the lack of transparency on how such estimates are obtained, which limits their practical applicability (Lam et al., 2023; Sutanto et al., 2020).

In the study of food insecurity, many authors have emphasized the importance of "shocks"; i.e., unexpected disruptions to a community's typical livelihood due to exogenous changes in food production and/or distribution (Enenkel et al., 2020). Most relevant for this work, the model of "dynamic resilience" (Peterson et al., 2018) emphasizes how the relationship between community livelihoods, agricultural production and weather catastrophes varies over time as a function of adaptation measures, resource stocks and other factors that can rarely be fully modeled. This dynamic or contextual nature of climate risk is apparent in studies which ask participants to self-report the impact of weather events – for instance, Guiteras et al. (2015) observes how in Bangladesh, farmers' reported impacts from a flood event bear a strong relationship with satellite measures of flooding in communities which rarely flood, but do not in communities in which flooding occurs routinely. This type of community-level adaptation is a significant mediator of climate risk, but is rarely accounted for in large-scale studies.

Prior work on the role of farmer perceptions in climate impact studies has largely fallen into one of two parallel literatures. One research agenda, focused on policy applications such as insurance, has noted the utility of farmers' recollected worst weather events as a heuristic way of "ground-truthing" policy (Blakeley et al., 2020; Brahm et al., 2019; Enenkel et al., 2020; Osgood et al., 2018). A large amount of this work has been confined to "grey" literature like policy reports due to its limited analytic scope (e.g. Madajewicz, 2013). A second agenda has focused on the social and behavioral determinants of farmers' climate perceptions, often conceptualized in terms of how they perceive trends (Dorward et al., 2020; Moyo et al., 2012; Mulenga et al., 2017; Osbahr et al., 2011; Osbahr et al., 2010) or make farming investment decisions under uncertainty (Gine et al; Patel, 2023; Zappalà, 2024).

Relatively little work has systematically studied patterns in farmers' historical recollections of climate shocks and how they relate to biophysical factors across a large spatial scale. This work contributes to that body of knowledge, drawing on the notion of farmer recall as a partial signal of information about climate impact proposed in Mauerman et al (2022). It also relates to the "impact-based forecasting" agenda that leading users of these functional estimates, such as the Red Cross, have advanced (Sutanto et al., 2019).

1.3. Study setting

This study focuses on the impact of drought on maize production in Zambia. Zambia typifies the ways in which changes in production systems can mediate the relationship between climate and livelihood shocks. Most notably, over the last 20 years, the government of Zambia has significantly invested in subsidized fertilizer for smallholder farmers under its Farmer Input Support Programme (FISP). This program was introduced in the wake of less than satisfactory maize production in the 1990 s culminating in the El Nino-induced drought that negatively affected maize yields in the 2001/2002 farming season. FISP was initially introduced in 2002 as the Fertilizer Support Programme and scaled up in 2011, and has led to a nearly twofold increase in average fertilizer usage per hectare among smallholders. The program is large-scale and has recently taken up as much as 10 percent of the government's annual revenues (International Monetary Fund, 2022), and has been associated with an increase in yields as well as with Zambia moving from a net importer to a net exporter of maize over this period (Burke et al., 2010; Mason et al; Mumba and Edriss, 2018).

Over the same period, Zambia has experienced a great deal of year-to-year weather variability, much of which is associated with multi-year tendencies in the El Nino Southern Oscillation (ENSO) cycle. El Nino events have driven some of the region's worst droughts in recent history (Pomposi et al., 2018). Previous work has noted how the coincidence of these major policy and weather events has confounded empirical attempts to isolate the impact of each (Burke et al., 2010; Jain, 2007; Kawaye et al., 2018). Most notably for this paper, Mulungu et al. (2021) observed temporal bias in estimates of the impact of rainfall on yield in Zambia that is likely due to the timing of these policy changes. Fig. 1 shows an overview of these trends – a steady expansion in maize production has coincided with an increase in fertilizer usage (the introduction and scale-up of FISP noted in the dotted lines). At the same time, these long-term adaptation trends coincide with multi-year cycles of good and bad weather conditions as measured by the official FISP drought index (the bottom panel). In such a setting, it is difficult to parse out the effects of weather on yields from the effects of adaptation measures.

Zambia also has a great deal of spatial diversity in its agricultural production systems, with three official agro-ecological zones which differ in their climatology, topography, typical cropping practices and typical scale of farming (Mulungu et al., 2021). The agro-ecological regions (Fig. 2 below) are mainly defined by the amount of rainfall

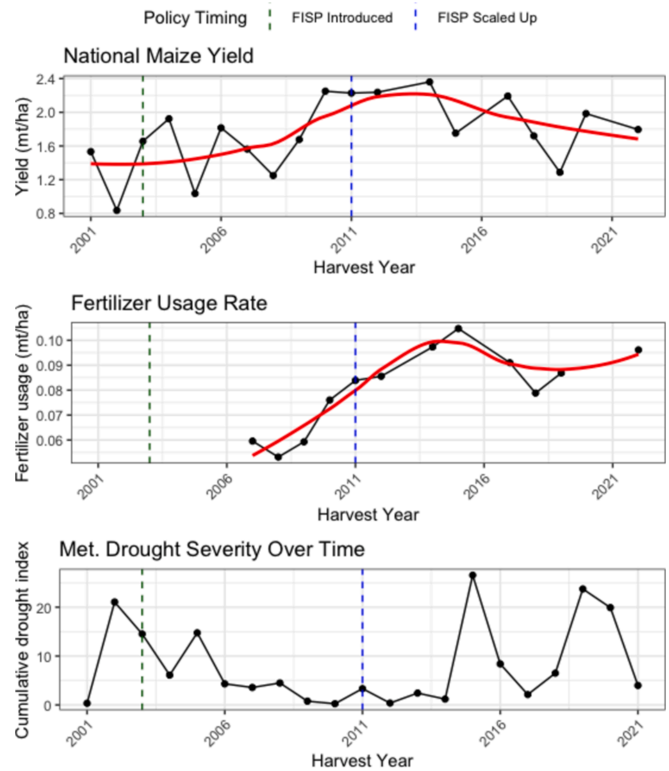

Fig. 1. Recent trends in national maize yield, fertilizer usage, and meteorological drought severity in Zambia.

received. Region I is characterized by having low rainfall and arid conditions. Region II is determined by having moderate rainfall while Region III receives the highest amount of rainfall.[1] Farmers in Region III tend to have higher yields per hectare but cultivate relatively less land; commercial farming is beginning to emerge here, but is still relatively uncommon. Farmers in Region II tend to be larger-scale producers with consistently higher yields – this is the only part of the country where commercial farming is currently practiced at significant scale. Finally, Region I has the lowest yields of any part of the country, but a moderate amount of cultivated area (see Appendix D for further descriptive details of spatial patterns in production, including differences in planting timing, landholding size, fertilizer usage rate and crops cultivated).

We focus on maize for this study, as it is by far the most widely grown crop in Zambia, the most important for livelihoods, and the most consistently measured. Compared to other crops, disruptions in maize production tend to be the most salient event to many farmers (compare (Dakurah and Osbahr, 2023)) and tend to be most disruptive for the wider economy. Maize price dynamics constitute a major driver of overall inflation in Zambia (Chapoto, 2014). Furthermore, even though in principle FISP is available to all crops, in practice it has tended to favor the production of maize, which is another motivation for focusing on it. Likewise, we focus on drought for its relative importance and its relative ease of measurement as compared to other hazards like excess rainfall or flooding. While these choices were made for analytical clarity, there is room for future work to explore a greater diversity of crops and hazards.

As part of FISP, farmers pay into a parametric drought insurance scheme. This scheme has faced difficulties in developing a parametric measure of drought that is robust to farming differences over space and time ("2021- Technical Report on Zambia's Farmer Input Support

[1] Strictly speaking Region II is further divided into two sub-classifications, IIa and IIb, based on the amount of rainfall received and the topography.

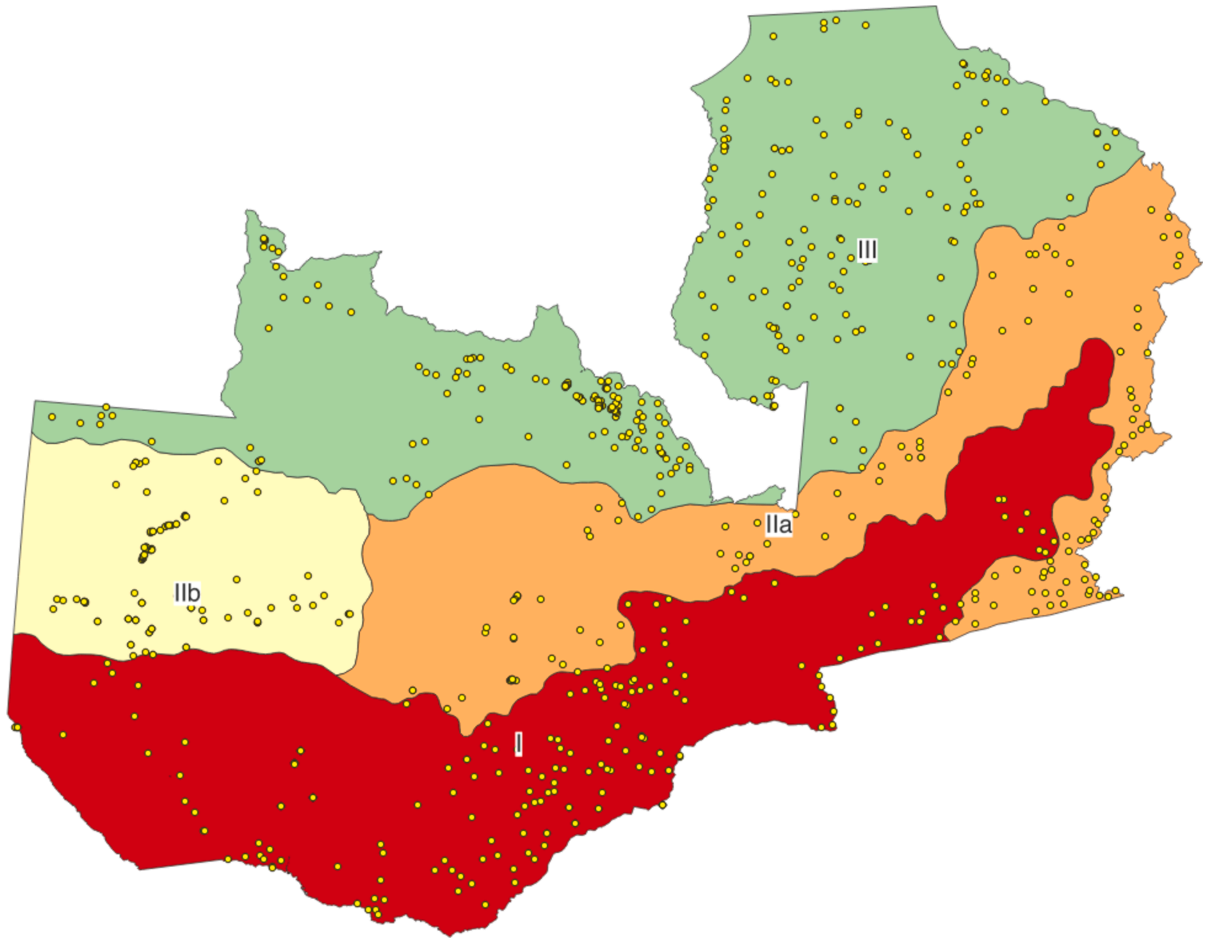

Fig. 2. Farmer focus group sites (yellow) and official agro-ecological zones. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Program (FISP) Index Insurance Product Improvement | World Food Programme," 2021). It is with these practical difficulties in mind that the Zambian government conducted a large-scale community survey of farmers' historical climate impacts in 2021, which provided the core data for this study.

By studying how farmers' recollection compares to the government drought severity index, we can triangulate which weather events were the most significant in context, and estimate the degree to which this self-reported data is a reliable proxy for shocks. We can further compare this approach to measuring drought shocks against the typical approach of regressing weather on yields, and quantify that method's probable bias or inefficiency from omitting adaptation factors like the expansion of FISP.

2. Methods and materials

2.1. Hypotheses and methodology

Our formal analysis proceeds in two parts. The hypothesis statement for each, and its accompanying statistical test, are as follows:

2.1.1. H1: Farmers' recollected drought shocks exhibit discernible patterns over space and time that reflect differences in weather and factors of production

For H1, we wish to understand whether farmers' recollections reflect a statistically identifiable signature of major climate shocks, or whether they are indistinguishable from noise. We do this by partitioning both the farmer and weather data into distinct axes of variability using principal component analysis (PCA), then comparing the similarity of the dominant spatiotemporal patterns from each dataset.

By using a variance decomposition method like PCA, we allow the data itself to tell us which patterns of spatiotemporal variability best characterize it, without imposing any ex ante structure. We chose PCA as a statistical method for H1 because it has commonly been used in climatological analysis to identify distinct patterns of spatial variability in weather (along with similar techniques like empirical orthogonal functions) (Hannachi et al., 2007), as well as in survey data analysis to identify distinct response profiles to a large number of survey questions (Desarbo et al., 2007).

PCA partitions out the distinct (i.e., orthogonal to one another) linear combinations of variables which explain the most variation in a dataset **(Equation (1)**:

$$\mathbf{T} = \mathbf{X}_{\mathbf{i}=1\ldots\mathbf{n},\mathbf{j}=1\ldots\mathbf{p}}\mathbf{W}_{\mathbf{j}=1\ldots\mathbf{p},\mathbf{l}=1\ldots\mathbf{L}} \tag{1}$$

Where X is the original data matrix of n observations over p features, W is a matrix of basis vectors transforming the p features into L orthogonal combinations (henceforth, the feature "loadings"), and T is a re-projected version of X in which each observation n has been projected onto the basis vectors of W (henceforth, the observation "coordinates").

In this case, we first code the farmer and weather data to be commensurate in scale. In both datasets, each row represents a district, and each column (feature) represents one agricultural year, 1983–2020. Column values represent the relative drought severity of that year in that place. The worst year is coded with a value of 8, the second worst year a value of 7, and so on down to the 8th worst year. Years that are not among the worst drought years are all coded as 0; i.e., not bad but not differentiated from one another.

After applying PCA to the farmer focus group information, we ask whether the first several components explain a meaningful amount of variance in the data, and if so, whether those components correspond to coherent patterns over time and space. We do this by comparing the first several principal components from the farmer data to those from a comparable analysis of the weather data. If farmer recall is meaningful and not just noise, we would expect areas with distinct climate vulnerabilities (in terms of weather shocks but also cropping practices, farm size, input use, etc.) to present distinct principal component patterns in an analysis of the recall data. We quantify this through the Spearman correlation between the farmer and weather principal component coordinates of each observational unit (district). We also cross-reference these findings with what we know about geographic differences in farming systems, as described in **Section 1.3**.

Furthermore, we would expect that the specific years that farmers in each region recall as the worst would also be among the relatively driest years in terms of weather. We quantify this by estimating the correlation between the year-by-year farmer and weather principal component loadings, which tell us which years drive the distinctiveness of each component.

2.1.2. H2 conventional estimates of drought shocks using a regression of weather on yields are biased and / or inefficient due to the omission of adaptation factors

For H2, we wish to understand whether estimates of drought shocks based on yield–data alone – the 'status quo' approach – would lead to estimates which are biased and / or inefficient due to the omission of adaptation factors which vary over time – namely, the large-scale introduction of fertilizer subsidies under FISP.

We test H2 by comparing different panel regression specifications of yield and weather measured over districts (i) in each year (j). **Equation (2)** represents the "status quo" approach – a regression of weather on yield and a linear trend term.

$$\text{yield}_{i,j} = \beta_1 \text{drought}_{i,j} + \beta_2 \text{year}_j + U_i + \varepsilon_{i,j} \tag{2}$$

Where U is a district-specific random effect and e is a Gaussian error term.

We use a random effects model for this and the subsequent specifications, as weather should be exogenous from the district-specific idiosyncratic effects; this assumption is supported by a Hausman test (shown in Appendix F).

We compare this "status quo" specification against two different models which attempt to account for adaptation factors. **Equation (3)** includes lags of yield in the regression, meant to account for un-modeled time-dependent processes like the fertilizer subsidy amount in that district. We use a lag order of 3, based on the observed autocorrelation structure in yield (shown in Appendix F).

$$\text{yield}_{i,j} = \beta_1 \text{drought}_{i,j} + \beta_2 \text{year}_j + \phi_{1,2\cdots n} \text{yield}_{j-1,j-2\cdots j-n} + U_i + \varepsilon_{i,j} \tag{3}$$

Equation (4) directly includes the fertilizer usage rate per hectare as an explanatory variable. Since this information is only available from 2007 onward, our available time series data is short, and thus lags are omitted.

$$\text{yield}_{i,j} = \beta_1 \text{drought}_{i,j} + \beta_2 \text{year}_j + \beta_3 \text{fertilizer}_j + U_i + \varepsilon_{i,j} \tag{4}$$

If adaptation factors are relevant, the status quo model may exhibit two significant issues. The first potential issue is bias in the estimates of weathers' effect on yield due to spurious trends. For example, the expansion of FISP coincided with a multi-year period of good rainfall. This may lead to systematic over- or under-estimation of weather shocks to agricultural livelihoods.

The second potential issue is inefficiency – that is, inaccurate estimates of the regression coefficient standard errors due to serial correlation. Inefficiency can arise even when the regression is asymptotically unbiased, and serial correlation tends to lead to over-confident estimates. This is a particularly salient issue in relatively short time series like the one used for this paper (Wooldridge, 2002).

We test for bias in the conventional approach to estimating shocks by comparing the size of the weather coefficient in our various specifications. If there is no bias from omitted adaptation factors, then the coefficient should only change minimally between specifications. However, if it is very different in the status quo model than the others, there is likely bias.

We test for inefficiency in the conventional approach by using the panel Breusch-Godfrey test for serial correlation in errors (Wooldridge, 2002). If the null hypothesis of the Breusch-Godfrey test is rejected, it means that there is serial correlation in the error structure, and the standard errors of the regression coefficients are inaccurate, meaning the model may be over-confident.

Since our district-level time series is fairly short, we supplement our analysis by comparing **Equations (2) and (3)** in the province-level version of the CFS data, which goes back to 1987 on a coarser spatial scale.

2.2. Data

We spatially averaged all data to the district (administrative level 2) level, and temporally aggregated all data to the year level. We code all data according to the year of harvest – for example, the data associated with "2015" includes the measured drought severity over the 2014/15 rainy season, the yield statistics for the 2015 harvest, and farmers' recollection of how severe the drought was during that agricultural year.

2.2.1. Farmer recall data

Our primary source of data is the perspectives of farmers themselves. This data comes from a nationally representative survey of 925 farmer focus groups held in 2021, collected by Ministry of Agriculture extension workers and supported by the World Food Programme.

The primary goal of this survey was to obtain a participatory ranking of the 8 worst drought years out of the period 1983–2020 in each community's perspective. Data was collected using a consensus-based focus group methodology in which 20–30 participants per village were first asked to discuss the question in small groups, and then convene to compare the groups' results. Any discrepancies between the groups' rankings had to be reconciled through community discussion. In this way, the survey aimed to identify which drought events were the most salient in each community, without the need to precisely estimate the amount harvested in each year (which is known to exhibit significant noise and bias in self-reported surveys, and may not be the only relevant aspect of how farmers experience drought).

The survey also collected data on farmers' cropping practices, including the community's typical cropping calendar. Surveyed villages were selected on the basis of being geographically representative of where the majority of farmers live in each district, with a minimum of 4 villages per district (spatial distribution shown in Fig. 2**)**. The full survey protocol is described in Appendix B.

2.2.2. Agricultural production data

Our data on agricultural inputs and outputs comes from the Crop Forecast Survey (CFS) that is conducted by the Zambia Statistics Agency. The CFS, which has been conducted regularly since the 1980 s, is based on annual surveys of select farmers in each district of the country. The results of these surveys are used by the Ministry of Agriculture in conjunction with census data to extrapolate the total amount of each major crop that is harvested that year (in kg) and the total amount planted (in Ha). Since 2007, the CFS has also included data on fertilizer usage and disaggregated its results by small-scale and large-scale producers (the latter defined as those cultivating > 20 Ha of land). The full CFS methodology is described in Appendix C.

We use district level maize yield (kg/Ha) as our primary measure of agricultural productivity in this study. Our analysis period for studying yield begins in 2000, since gaps in the data and changes in administrative designations make systematic analysis at the district level difficult for earlier years. There are two post-2000 years with missing CFS data: the 2015/16 and 2020/21 harvest seasons.

Importantly, these limitations on data length and availability are typical of the ground-truth data commonly used for climate impact studies in the Global South. Since we wish to understand the biases that might arise from using such data as the basis for measuring livelihood shocks, these limitations are salient to the hypotheses of the paper. However, to test our statistical findings for robustness, we supplement our analysis by looking at data on the province level, which goes back – with less geographic precision – to 1987.

Note that the CFS uses the 2000 Census district definitions to ensure measurement consistency over time. Any other data (like drought severity) that were measured using a more recent set of district boundaries were first aggregated to the 2000 Census district level.

2.2.3. *Weather data*

Our data to measure drought comes from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset (Funk et al., 2015), a gridded statistical composite of satellite-estimated precipitation and weather station precipitation.

To transform CHIRPS into an annual measure of drought severity, we apply a drought index methodology based on the one used for parametric drought insurance as part of FISP. The methodology, documented in full in Appendix A, is based on measurement of rainfall deficits during two crucial periods of the year – one around the time of maize sowing, and another around the time of tasseling. For each of these periods ("windows"),cumulative rainfall is first computed by year, 1983–2020, and then the driest 20th percentile of the historical data is calculated. This quantity defines the "trigger" – the level of rainfall deficit below which we count the year as a drought. As rainfall decreases, the drought severity index increases linearly, reaching 1 at the driest recorded amount on record. We compute this index separately for each window, then average the window-level indices together to arrive at our final drought proxy, which is thus normalized to each area's climatology.

The specifics of this drought index were determined in consultation with stakeholders in the Government of Zambia, World Food Programme Zambia, and participating insurance companies, and thus represents a locally validated approach for determining drought severity. Most notably, the timing of the windows in each district were tuned by local experts to reflect differences in cropping practices between areas.

3. Results

3.1. *H1 – Coherence of farmers' perceptions*

If farmers' recall is a reliable source of data on climate impacts, we would expect it to exhibit a couple of important qualities. First, we would expect it to show coherence over space – that is, neighboring farmers who experience similar climate shocks and use similar agricultural factors of production should report similar answers. Second, we would expect it to show coherence over time – that is, within a region, there should be some degree of correspondence between farmers' consensus years and the worst measured droughts in that region.

To address both of these questions, we use the presentation of PCA to show which features, i.e. years, explain the predominant patterns of variation between districts. We follow this process for both the farmer recall data and the drought index data, each of which have been normalized to express a ranking of the worst 20 % of drought years in a given district, and compare / contrast them.

In both datasets, the first three principal components explain a majority of the variance (50 % in the case of farmer data, 76 % in the case of drought data), so we retain only those three components for the subsequent analyses.

Fig. 3 shows the coordinates of the first three principal components in the farmer data (top panel) and drought index data (bottom panel). These coordinates tell us which geographic areas are associated with distinct combinations (i.e., components) of worst years. In both datasets, the first component identifies droughts which are commonly felt across most of the country; the second component identifies droughts with a differential impact between the east and west, and the third component identifies a similar gradient between the north and south.

The coordinates of these three principal components in the farmer and drought datasets are highly correlated across space (Table 1), and are consistent with geographic differences in farming systems (as detailed in the Study Setting). The first components (nationwide droughts) have a 70 % correlation over space; the second and third components (east/west only and north/south only droughts) have a 38 % and 43 % correlation, respectively. Thus, we can conclude that the dominant patterns in farmers' recall over space are consistent with the dominant patterns in climate shocks.

The Table 1 results tell us that the two datasets are correlated over space, but do not tell us which specific years farmers tend to recall as bad. It may be the case that the two datasets are spatially correlated *not* because farmers' recall is related to bad weather, but because of some unrelated factor imposing patterns over space, such as which enumerator team carried out the survey in each province. Thus, we also want to compare the principal component loadings; i.e., which years drive the distinctive patterns in each dataset. Fig. 4 shows this comparison, with the drought component loadings on the X axis and the farmer loadings on the Y axis. If the two datasets identify similar years, then the X-Y plot should show a positive, linear relationship – that is, the worst years that are distinctively associated with a particular region should be similar in both datasets.

We see that not only were years with larger overall droughts more likely to be mentioned by farmers (Component 1, in green below), e.g. 2001 and 1999, but also that years with differential drought impact between the east and west (Component 2, in orange below) are reflected in both datasets, e.g. 1993 and 1994. This leads us to conclude that farmers' recall is not only spatially coherent, but reflects specific historical events of interest in that time and place.

The strength of correlation in year-by-year loadings (Table 2) varies by component. PC1 (country-wide droughts) and PC2 (east–west gradient) have a strong and positive correlation (54 % and 49 %, respectively), while PC3 (north–south gradient) has a near-zero correlation. This may be explainable by differences in farming practices and climate vulnerability across the country – farmers in the north are the least exposed to drought, and thus their recall may bear the least empirical relationship to anomalies in rainfall. Appendix E presents a full cross-correlation analysis between each pair of components.

Notably, we also see that farmers' worst years are relatively spread out over the recall period (1983–2020) and are not clustered around the most recent years. Furthermore, farmers' worst years tend to be associated with multi-year climate cycles like ENSO (visualized and described in **Section 1.3**). These findings suggest that farmers' perceptions are *not* subject to recency bias, in contrast to what some other studies of farmer perceptions have found.

We can further explore these findings by imposing a discrete classification on the PCA results, and examining the patterns and trends in agricultural output within each distinct farming region that results. We do this by applying a k-means classification with a k of 3 to the farmer principal component coordinate dataset. This yields a classification into southern, northern and central areas **(**Fig. 5**)** which broadly mirrors the three official agro-ecological zones **(**Fig. 2**)**. This similarity in patterns further suggests that farmers' recollected shocks are related to the agro-ecological factors of maize production.

Using these region designations, we identify the years of strongest farmer consensus within each region since 2000 (when consistently measured yield data became available), and compare them against aggregate maize yields and weather, as shown in the top and bottom

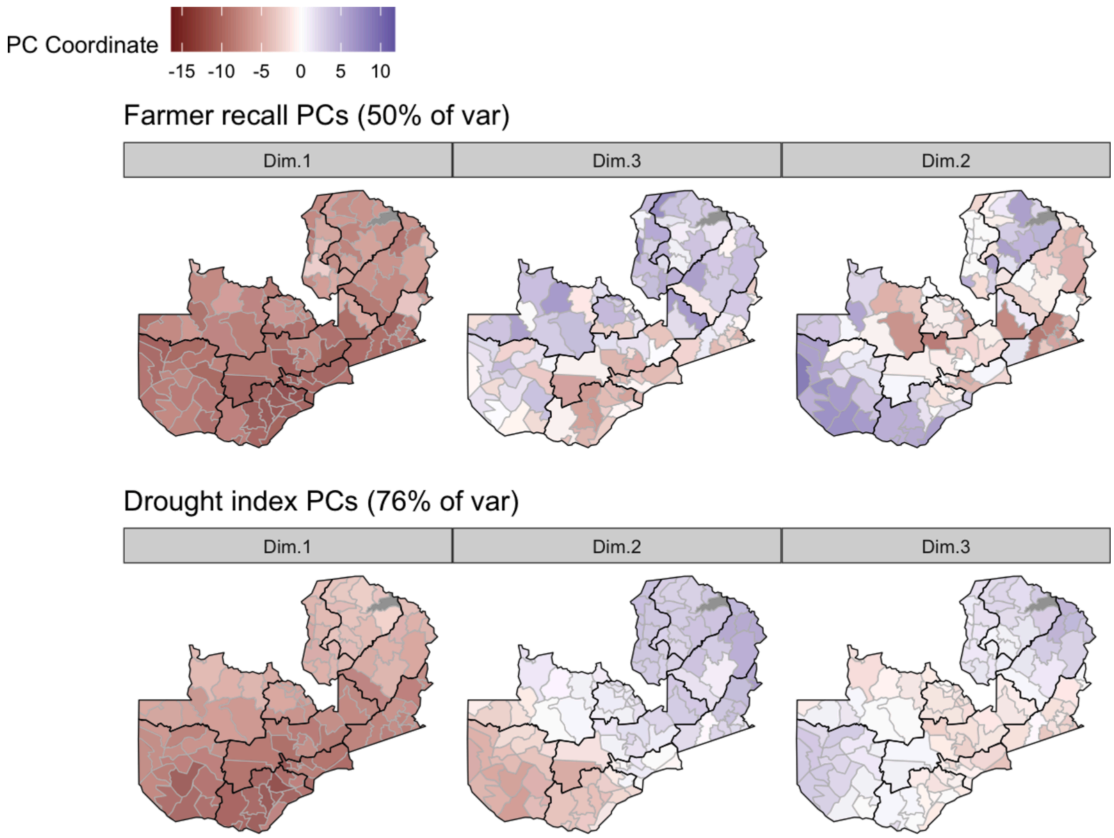

Fig. 3. Principal component coordinates of farmers' recollected livelihood shocks and meteorological drought shocks.

Table 1
Spearman correlation of farmer and drought principal component coordinates both overall and for PCs 1–3.

Principal Component	Coordinate Correlation
PC1	0.709***
PC2	0.385***
PC3	0.432***
Overall (PC1-PC3 Pooled)	0.780***

*=p < 0.1,**=p < 0.05,***=p < 0.01.

panels of Fig. 6, respectively.

A couple things are immediately apparent from this figure. First, we see that *within* each time period and region, farmers' worst years are related both with drought and with a year-on-year decline in yields. Second, we see that *between* regions and time periods, the absolute level of agricultural productivity associated with a drought shock varies greatly.

These observations comport with previous work that finds that household-level resilience is more related to year-on-year consistency in agricultural production than to absolute levels of production (Benso et al., 2023). They are also consistent with prior, more qualitative studies of farmers' climate recollections which find that the salience of specific "bad" years depends predominantly on what farmers *expected* to produce in that year, and less on *absolute* deviations in rainfall amounts or harvest quantities (Singh et al, 2018).

We cannot make a systematic statistical comparison between farmers' bad years and yields because of the differing lengths of the two datasets and the missing yield data. However, our H1 results suggest that farmers' recollected worst years reflect drought shocks across a variety of spatio-temporal contexts, even if farmers' recall is not an exhaustive inventory of all drought events (by construction, farmers could only rank the worst 8 years out of the last 40).

3.2. H2 – Bias in estimates of drought on yield

In H1, we established that farmers' recollected drought years have a strong statistical relationship with drought shocks over time and space, and that farmers' recall does not appear to exhibit recency bias. This suggests that farmers' recall is a reliable basis for establishing when and where major drought shocks occurred.

However, most previous work in the area of climate impact estimates has not considered or has not had access to such experiential data. Instead, the conventional approach to estimating drought shocks in agriculture is to use yield data as the basis for measuring impact, and to assume that weather exhibits a constant relationship to yield over time. As apparent from Fig. 1, this assumption is unlikely to hold in Zambia, where there have been large-scale changes in agricultural adaptation policy over the past decades.

In H2, then, we test whether estimates of the impact of drought based on yield data alone – the "status quo" approach to estimating livelihood impacts – are systematically biased and / or overconfident. If so, decisions derived from such models may not consistently reflect the conditions which are actually disruptive to farmers' livelihoods.

We test this by comparing our "status quo" model against two alternative specifications which attempt for account for adaptation policy. Table 3 shows the results:

The estimated coefficient of drought on yields is much larger in the status quo model (model 1) than in the other two (models 2,3). This suggests that there is likely bias in the status quo approach due to spurious correlation between weather, yields and the omitted factor of adaptation policy. Since data on the most salient aspect of adaptation policy – fertilizer usage – is only available from 2007 onward, we only have limited data with which to test this proposition directly (model 3). However, since the coefficients on the lagged values of yield likely pick up policy-related factors which are dependent over time, the second model tells a similar story to the third.

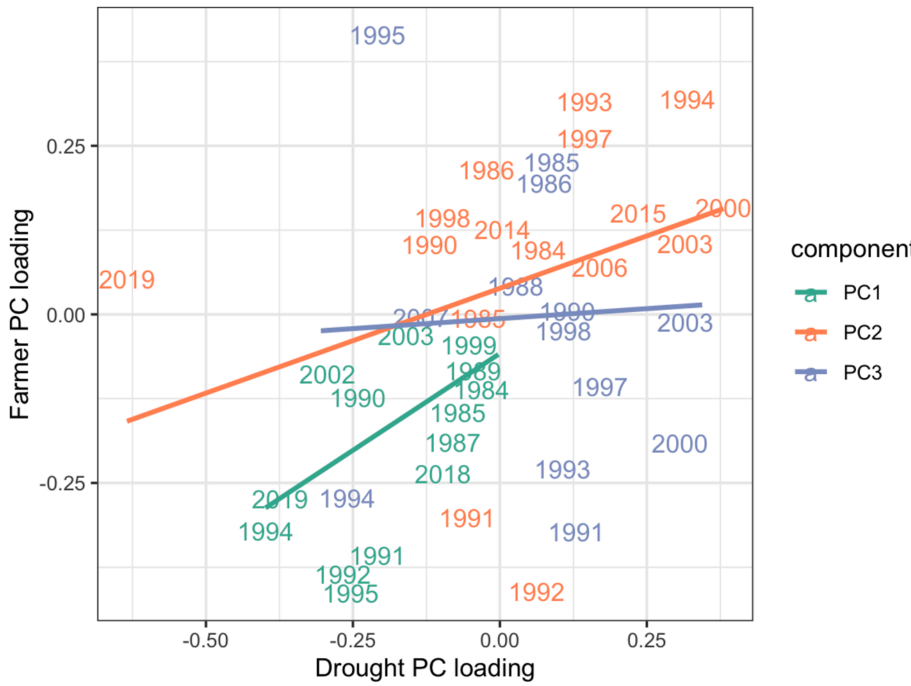

Fig. 4. Loadings of specific years in farmer and drought principal components, PCs 1–3. Solid line shows a fitted slope-intercept relationship between the drought index and farmer loadings for each component.

Table 2
Spearman correlation of farmer and drought principal component loadings both overall and for PCs 1–3.

Principal Component	Loading Correlation
PC1	0.544***
PC2	0.497***
PC3	−0.139
Overall (PC1-PC3 Pooled)	0.438***

*=p < 0.1,**=p < 0.05,***=p < 0.01.

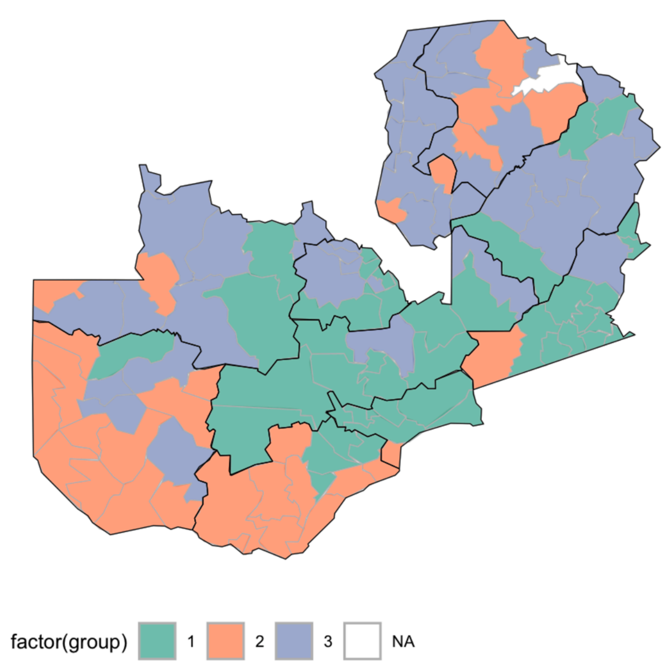

Fig. 5. "Region" designation derived from k-means classification of farmer bad year data with k = 3.

Table 4 shows a similar comparison with the province-level CFS data, which goes back to 1987 on a coarser spatial scale:

Over this longer time horizon, the estimated drought impact coefficient does not vary much with the inclusion of lags, suggesting that the biasing effect of spurious trends is diminished when more historical data is available. Notably, the drought impact coefficients in the Table 4 models are closer to those of the adjusted models in Table 3 than to the status quo model.

We can also test for potential inefficiency in the estimates arising from serial correlation in errors. Serial correlation due to the omission of time-varying factors like adaptation policy may lead to model estimates with an inaccurate degree of confidence (i.e., standard error), even when the model is unbiased. Table 5 shows the results of the panel Breusch-Godfrey test for nonstationarity of residuals in each model:

We see that the district-level models which include policy controls (2,3) do not exhibit serial correlation, while the status quo model (1) does. Both of the province-level models (4,5) exhibit serial correlation, suggesting there may be other un-modeled factors over this longer time horizon, or that it is harder to account for idiosyncratic policy effects through the inclusion of lags at this coarser spatial scale. Notably, however, the serial correlation is less for the model with lags (5) than the one without (4).

Taken together, these findings suggest that failing to account for adaptation factors in estimates of weathers' impact on agricultural yield would lead to impact estimates that are at least inefficient, and in some cases biased as well. Since many studies rely on these types of estimates to evaluate weather insurance, predict the probable impacts of climate change, or other decision support applications, these statistical issues have major practical implications for applied work. This failure to account for adaptation is particularly salient in settings with relatively little historical data on agriculture, as is common in the global South.

4. Conclusion

4.1. Takeaway messages

In the first part of the paper, we find that farmers' recollected worst

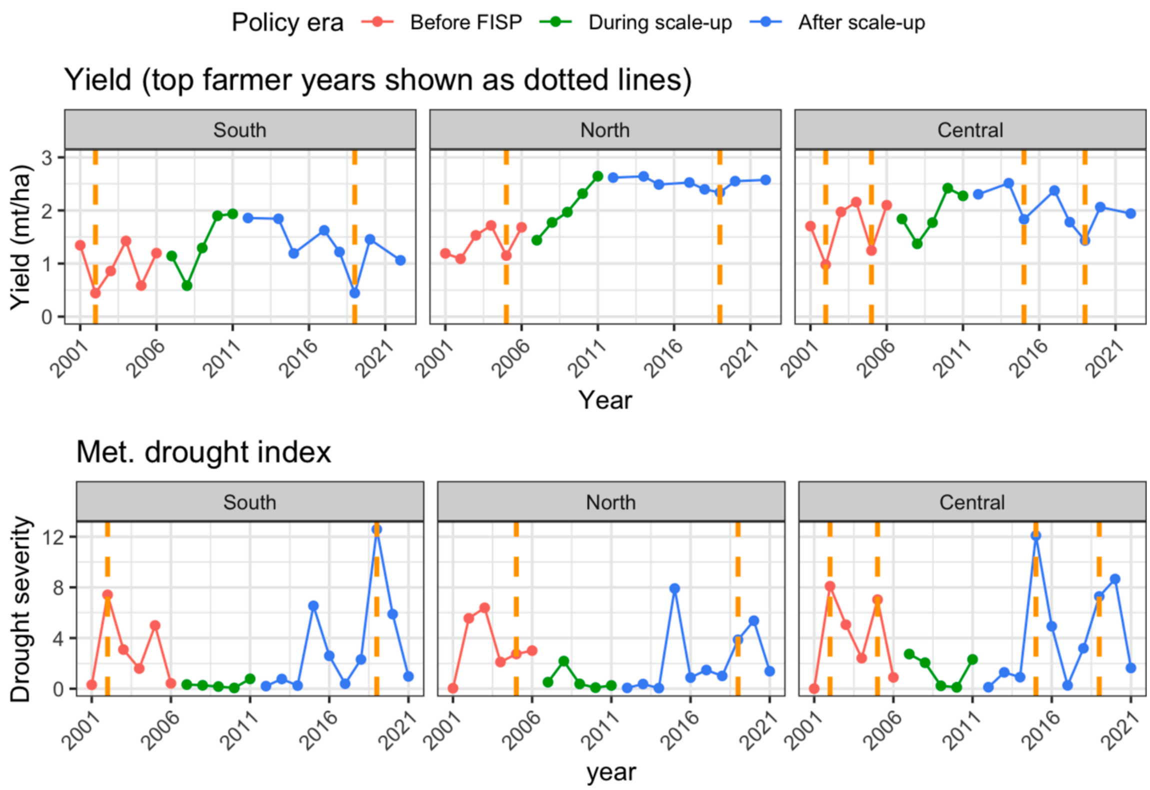

Fig. 6. Yield (top panel) and cumulative drought severity (bottom panel) in each farmer region. Farmers' top worst recollected years in each region shown as yellow lines. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Comparison of climate impact regression specifications using district-level yield data, 2000–2020.

	Dependent variable:		
	yield		
	(1)	(2)	(3)
drought	−2.689***	−1.498***	−1.643***
	(0.286)	(0.429)	(0.285)
lag(yield, 3)		−0.045	
		(0.035)	
lag(yield, 2)		0.192***	
		(0.039)	
lag(yield, 1)		0.483***	
		(0.036)	
fertiliser_rate			7.006***
			(0.224)
year	0.174***	0.005	0.118***
	(0.011)	(0.016)	(0.018)
Constant	2.184***	1.313***	0.955***
	(0.229)	(0.155)	(0.173)
Observations	1,204	833	808
R^2	0.208	0.381	0.565
Adjusted R^2	0.207	0.378	0.563
F Statistic	313.933***	509.831***	1,043.198***
Note:	*p < 0.1; **p < 0.05; ***p < 0.01		

Table 4
Comparison of climate impact regression specifications using province-level yield data, 1987–2020.

	Dependent variable:	
	yield	
	(4)	(5)
year	0.007**	0.004
	(0.003)	(0.003)
drought	−1.846***	−1.908***
	(0.307)	(0.286)
lag(yield, 3)		0.290***
		(0.051)
lag(yield, 2)		0.258***
		(0.051)
lag(yield, 1)		0.238***
		(0.052)
Constant	1.839***	0.460***
	(0.177)	(0.104)
Observations	306	303
R^2	0.124	0.522
Adjusted R^2	0.118	0.514
F Statistic	42.994***	324.639***
Note:	*p < 0.1; **p < 0.05; ***p < 0.01	

drought years are correlated with patterns of rainfall anomaly over space (similar areas experience droughts together) and over time (similar drought years are identified in a given area). This is the case even for years in the distant past, suggesting that farmers do not exhibit recency bias in their recall. The patterns in farmers' recall are also consistent with Zambia's distinct agro-ecological regions. Farmers' recall appears to be associated with year-on-year declines in yield, although we lack sufficient historical yield data to test this systematically.

In the second part of the paper, we find that a regression of rainfall anomaly on yield – a more typical approach to measuring livelihood shocks than asking farmers directly – would result in biased and

Table 5
Test for serial correlation in residuals for each model in Tables 3 and 4.

Model	Breusch-Godfrey test statistic	Serial Correlation?
Status quo, district (1)	167.3***	YES
Lags, district (2)	0.30	NO
Fertilizer, district (3)	6.67	NO
Status quo, province (4)	101.34***	YES
Lags, province (5)	67.64***	YES

*=p < 0.1,**=p < 0.05,***=p < 0.01.

overconfident estimates of weather's impact. Adding controls for adaptation policy reduces the bias. Using a longer (~35 years instead of 20) but less spatially precise data source on yields also reduces the bias, but this approach still exhibits inefficiency. These results underline how the lack of community-level, historically representative data on climate shocks can trouble the conventional approach to climate impact measurement, which relies on readily available administrative data like agricultural yields.

Taken together, our findings suggest that farmers' experiential knowledge of the worst drought events is a better basis for measuring community livelihood shocks than agricultural yields. The use of yield data is problematic due to the confounding effects of adaptation policy, which mediate the relationship between drought and agricultural output but are difficult to model, and the limited historical record of yield, which limits the number of observed rare drought events. In contrast, surveying farmers directly about which years had the worst drought shocks leads to a more representative sample of rare disaster events, and captures what matters to a community in spatio-temporal context.

4.2. Discussion & future work

Our findings suggest that using farmers' experiential knowledge to establish when and where the worst climate shocks occurred is a promising methodology, even in large-scale quantitative studies. Most past work in this area has relied on administrative data as the basis for measuring impacts, without considering how its limited temporal span or models' tacit assumptions of constancy may bias their findings. Asking farmers directly about what events mattered to them offers a way to fill in important data gaps when studying the human impacts of climate variability and change.

Our findings have implications beyond Zambia and beyond drought. The methodology of surveying farmers about their climate experiences in a semi-quantitative way could be applied to a variety of other contexts and questions. For example, the impact of flooding on agricultural livelihoods depends heavily on adaptation measures – some farmers are accustomed to and even rely on regular inundation, while others rarely experience flooding, and so any amount of water could be disruptive. The difference between the two is difficult to model with readily available sources of administrative or geographic data. Our ongoing work in Kenya and Bangladesh explores how data on farmers' self-reported flood impacts could improve remote sensing-based estimates of flood risk.

Our finding that farmers' recall is consistently related to livelihood shocks, even if the absolute amount of yield varies from event to event, stands in contrast to past studies which conclude that farmers' perception of the climate bears little relationship to observed conditions (e.g., Moyo et al., 2012). Importantly, many of those studies asked farmers to make statements about long-term climate averages or trends, rather than identifying specific years which mattered. The latter methodology may better comport with how farmers actually experience the climate – an epistemology which is more about "episodic" knowledge of particular events than about "semantic" knowledge of long-term summary statistics (per Sheppherd (2007)).

As more and more NGOs and governments adopt a "participatory" approach to addressing climate risk, this kind of local knowledge is of increasing relevance to practitioners working on climate adaptation policies that require community validation, such as agricultural insurance and anticipatory action. Focus group data is relatively inexpensive to collect, and can fill in knowledge gaps over time and space where administrative data is lacking. Thus, understanding how to work with it systematically is crucial – the formal statistical study of climate change has conventionally excluded such experiential data, as it does not comport easily with common methods of quantitative analysis.

Future work could explore a more systematic method for relating metrics of climate variability to farmers' recollected impact. Our findings in this paper show that there is *some* relationship between a simple drought index and farmers' worst years, but the specific aspects of climate variability that matter the most may vary from context to context. Future work could more rigorously quantify the statistical relationship between a range of climate metrics and farmers' impact at a local level using probabilistic methods. Such methods could form a more robust basis for bottom-up estimates of climate's impacts on agricultural livelihoods than administrative data alone.

CRediT authorship contribution statement

Max Mauerman: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Henny Osbahr:** Writing – review & editing, Validation, Supervision, Resources. **Emily Black:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Conceptualization. **Daniel Osgood:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Grieve Chelwa:** Writing – review & editing, Validation, Investigation, Data curation, Conceptualization. **Bernadette Mushinge:** Writing – review & editing, Validation, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Emily Black reports financial support was provided by National Centre for Atmospheric Science. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A. Drought index formula

The drought index used for this paper, which is based on the one used for parametric drought insurance in Zambia's FISP program, is based on the measurement of district-level CHIRPS rainfall during agriculturally important times of the year. A maximum 10-day value ("cap") of 50 mm / dekad is applied to the rainfall before calculation of the drought index, to smooth over any extreme rainfall values that are unlikely to be agriculturally beneficial.

Calculating the drought index involves three steps: 1) Computing trigger and exit values over each measurement period ("window"), 2) computing a 0–1 drought severity index for each window, and 3) averaging the windows' indices together to arrive at a single metric of drought severity.

Index triggers are calibrated with the goal of providing a meaningful payout for the worst 20 % years in the historical record of 1983–2020. The exit is likewise based on the value of the driest observed year in the historical record.

To address the key times of the season, 4 separate index windows have been developed: An early and a late simple sum window, and an early and a late rolling average window. For the sum windows, which are meant to capture prolonged rainfall deficits during agriculturally important times of the year such the maize planting and tasseling period, the formula below determines the 0–1 drought severity for a given trigger and exit value:

$$Severity = (1 - ((Capped\,Rainfall\,Sum\,Over\,Window - Exit) / (Trigger - Exit)))$$

While for rolling average windows, which are meant to capture any brief dry spells over a longer measurement period, the formula is:

$$Severity = (1 - ((Min(2\,Dekad\,Rolling\,Average\,of\,Rainfall\,Over\,Window) - Exit) / (Trigger - Exit)))$$

The final drought severity index is an average of the four index window severity values.

The timings of the measurement windows were determined by local government and insurance company stakeholders in a participatory process, and were based on analysis of farmers' cropping calendar in each district, as well as how well the potential index would capture farmers' reported historical bad years. The window timings vary by district, and a full table is available on request. A summary of the range of possible timings is as follows:

Table A1
Minimum-to-maximum range of drought index window timings.

Window	Start Time	End Time
Early Sum	Oct 21-Jan 21	Dec 1-Feb 21
Late Sum	Dec 1-Mar 11	Jan 21-Apr 21
Early Rolling	Nov 1-Dec 1	Dec 1-Jan 21
Late Rolling	Dec 21-Feb 21	Mar 1-Apr 1

B. Farmer survey protocol

The protocol followed for the farmer focus groups is reproduced below:

For this exercise, farmers will identify the worst drought years and they will discuss the reasons why they were the worst. During this exercise, farmers will name the worst drought 8 years (that they can remember) in the past ~ 40 years (the period 1983–2020) for their primary crop.

Fig. B1. Example of Flip Chart for Interactive Exercise

- Assign participants in groups of 4–5 people. At least one person in each group should be able to read/write (can be a farmer or an assistant). Provide each group with several post-its of the same color (or other objects suitable to use in the field). Each group should have 3–6 post-its.
- Ask each group to select a representative who would be responsible to place the post-its in the appropriate place on the board once the group reaches consensus on the worst 8 years.

- Discuss with the farmers and the participants to identify which part of the season caused the loss in production: early, late, or both. It's important to know which months the farmers consider part of the "early" season and which months correspond to the "late" season.
- Explain to each group that this is an interactive exercise where participants in each group must discuss which years were the worst, based on their experience and memory. Ask each group to discuss and identify the 8 worst years. The eight worst years will be represented by the post-its each group receives (or other objects that groups receive). The groups should rank the worst years (with the worst year being 1). Remember to designate the elected group representative to lead the discussion.
- Give the groups 30 min to decide on the worst 8 years.
- Now, ask the group representative to walk to the chart and place the post-its next to the worst years decided by his/her group.
- After all groups have placed all their post-its on the flipchart, compare the years reported by the different groups. If there are differences, give the participants a chance to discuss in one big group until they reach agreement on 8 common worst years going back to 1983.
- Groups will also have to specify if the rainfall was particularly low at the start or at the end of the season. The facilitator can give an example like: "If you had the worst year for your main crop because of a drought, was the precipitation lower than usual in the early or the late part of the rainy season?"
- From all the years that the farmers listed, select the years for which there was strong disagreement between the farmer groups, and discuss the effects of the worst years until consensus is reached.

C. Yield data protocol and QC

C.1 Yield data protocol

The yield data used for this paper comes from the Government of Zambia Crop Forecast Survey (CFS). The following description of the dataset comes from the Zambia Statistics Agency website:

The CFS obtains estimates from agricultural holdings (farmers) on the area under major crops as well as expected production and sales estimates, quantity and variety of seed, type of fertilizer used, carry over stocks, crop marketing and labour costs, among others during the season. The production estimates that are generated are used to assess the food security situation in the country and also to develop the National Food Balance Sheet (NFBS), which is used to determine the surplus or deficit of major cereals and tubers in the country.

The CFS covers all provinces of the country and is conducted in what ZamStats calls Enumeration Areas (EAs). A sample of EAs involving agricultural households is drawn using probability proportional to size sampling scheme. The EA is the smallest area with well-defined boundaries identified on a census map. A total sample of 680 EAs are allocated nationally to each province and district proportional to its size (in terms of households). Twenty households are randomly selected from each of the 680 EAs in the sample and interviewed in detail.

The CFS covers three categories of agricultural households namely: Small-scale farmers, Medium-scale farmers and Large-scale farmers. The Small and Medium scale farmers are covered on a sample basis while the Large-scale farmers are covered on a 100 percent basis. A fixed number of 20 households are canvassed in each selected EA for Small and Medium scale farmers. The Large-scale farmers are captured in a separate sub-survey under the CFS on a 100 percent enumeration basis.

A Small-scale household is defined as a household cultivating 4.99 ha of area under crops or less. Households cultivating between 5 and 19.99 ha of area under crops are classified as Medium-scale households. All households cultivating 20 or more hectares of land and/or raising a specified number of poultry and/or livestock are classified as Large-Scale farmers.

The CFS collects information on area planted for each crop, expected production and sales, seed type, tillage method used, acquisition and usage of fertilizer etc. This information is based purely on farmer recall and estimation. The survey does not involve area measurement or direct field observation by the data collector as there are no field visits conducted. One of the reasons for relying on farmer recall and estimation is to reduce on measurement bias and error by the data collector.

Area expected to be harvested is also collected but is not used in the computation of yield. Only the area planted is used in yield computation. Yield is not calculated by the farmer but by the analysts at the data analysis stage. Yield is derived from quantity of expected production divided by the estimated area planted for each crop.

C.2 Yield quality control checks

To verify the quality of the CFS, we compare it against an independently measured source of data on maize yields: A nationally representative sample of crop cut data collected by the insurance company Pula during the 2021/22 season. This dataset, which is publicly available, covers a nationally representative sample of farming areas:

Fig. C1. Farmer focus group sites (yellow), Pula crop cut sites (green), and estimated WorldPop population density (white).

If the CFS is a reliable source of data, we would expect it to be broadly consistent with the Pula dataset in terms of which areas presented above- or below-average maize yields during the 2021/22 season. To determine this, we normalize both datasets against the 1987–2020 provincial mean and standard of yield from CFS to obtain a yield anomaly z-score, and compare their spatial similarity:

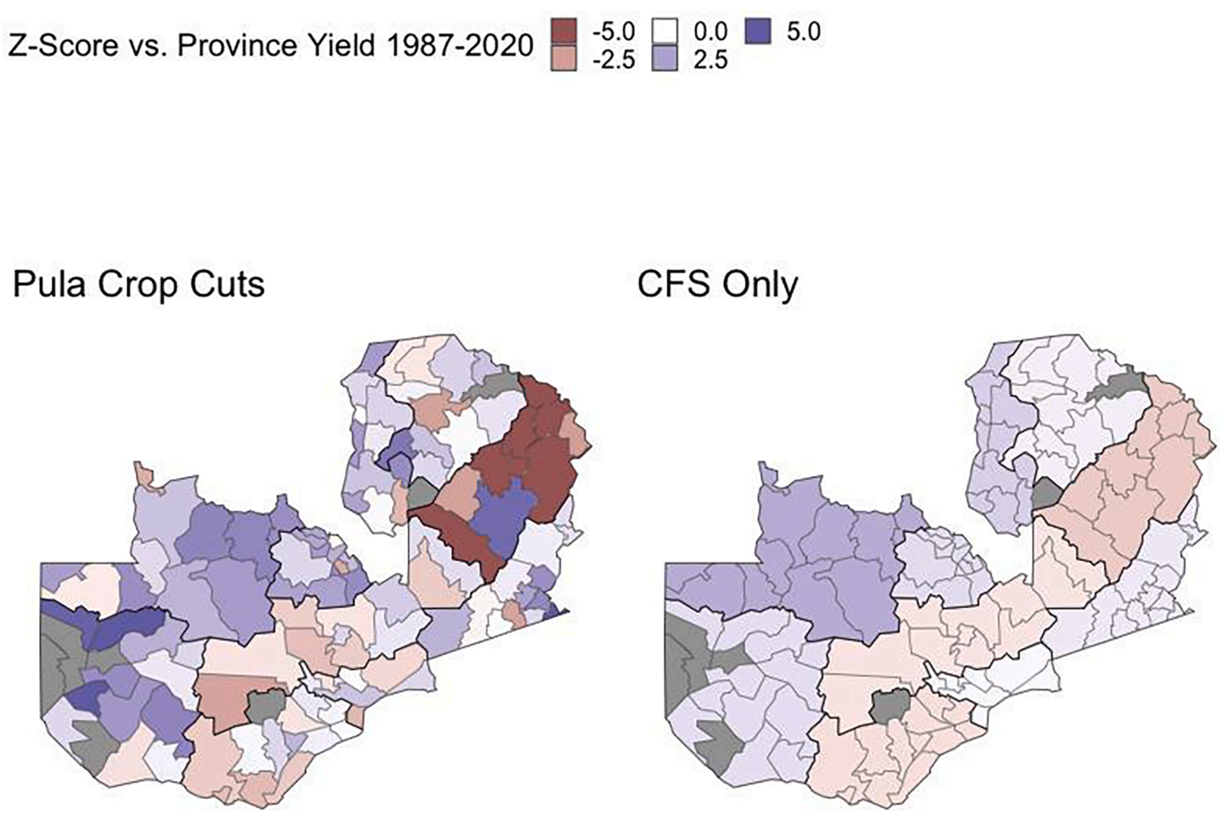

Fig. C2. Comparison of Pula and CFS maize yield anomaly estimates for the 2021/22 season. Gray areas indicate missing values for that district.

We see that the two datasets indicate similar areas as above or below average yield for the 2021/22 season. This leads us to believe that the CFS is a sufficiently reliable source of data to be used for historical analysis.

As detailed in Appendix F, historical CFS yields also have a physically plausible and statistically significant relationship with both measured drought and fertilizer usage, suggesting that consistent mis-reporting of yields is unlikely.

D. Descriptive plots of farming practices

D.1 Time series of agricultural inputs and outputs for small vs. Large-scale farmers

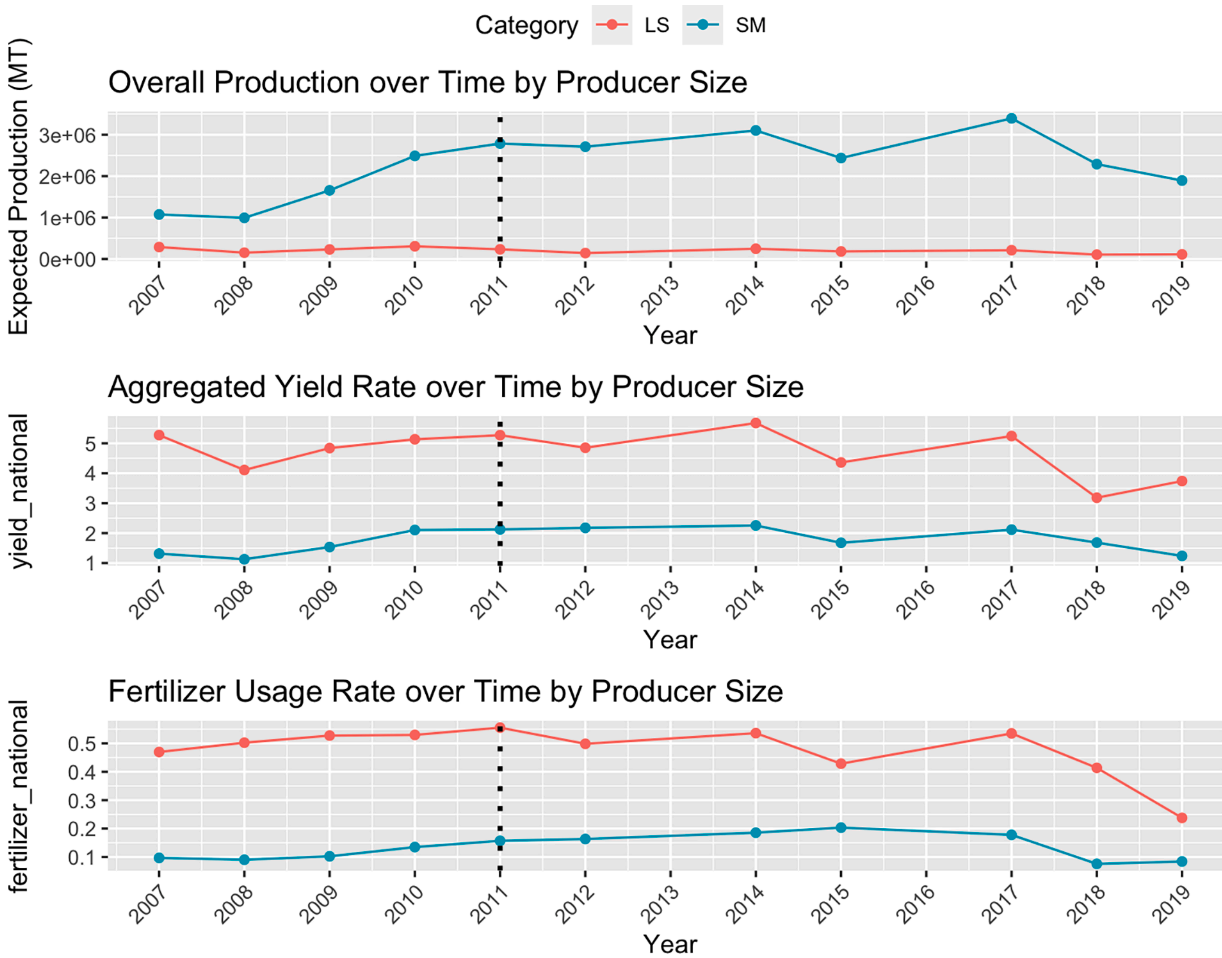

Fig. D1. Planted area, yield and fertilizer usage rate for small- vs large-scale farmers, 2007–2019.

D.2 Map of small-scale contribution to production

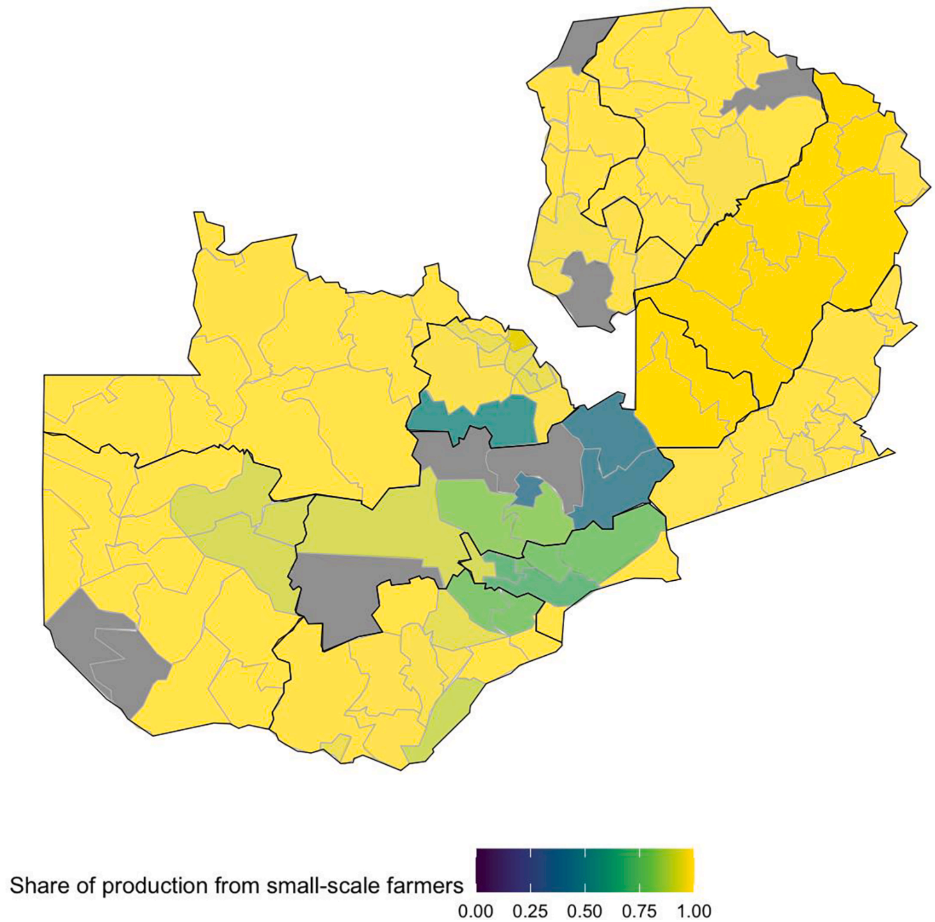

Fig. D2. Average share of maize production from small-scale farmers, 2007–2020.

D.3 Map of typical planting and harvesting time

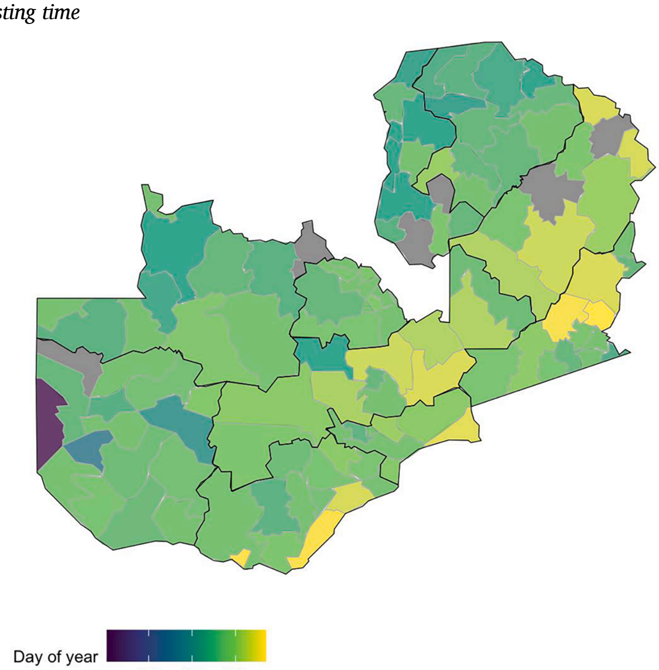

Fig. D3. Earliest day of planting period from FISP farmer surveys.

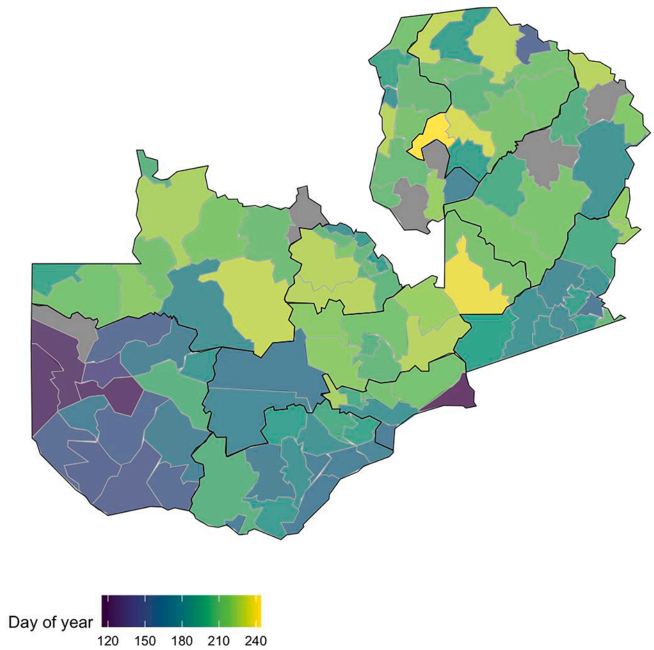

Fig. D4. Latest day of harvesting period from FISP farmer surveys.

D.4 Map of crops grown

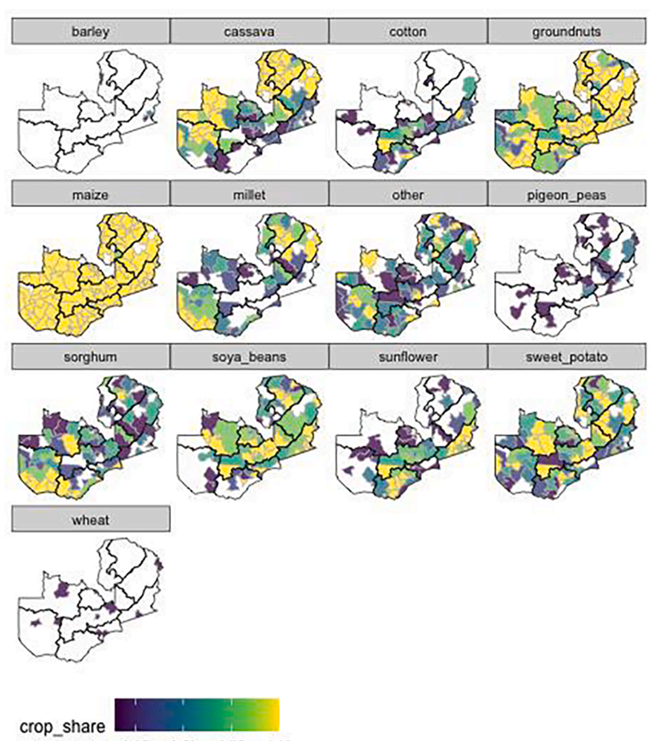

Fig. D5. Share of villages reporting growing various types of crops, from FISP farmer surveys.

E. Full H1 results

E.1 PCA variance explained

.

Table E1
First 10 principal components for drought data.

PC #	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	0.67	0.27	0.17	0.15	0.14	0.13	0.12	0.11	0.10	0.10
Proportion of variance explained	0.62	0.11	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.01
Cumulative proportion	0.62	0.73	0.77	0.80	0.83	0.85	0.87	0.89	0.91	0.92

Table E2
First 10 principal components for farmer bad year data.

PC #	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	11.60	5.33	4.60	4.38	4.02	3.85	3.69	3.58	3.38	3.27
Proportion of variance explained	0.35	0.07	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.03
Cumulative proportion	0.35	0.42	0.47	0.52	0.57	0.60	0.64	0.67	0.70	0.73

E.2 Cross-correlation matrix for first 3 PCs

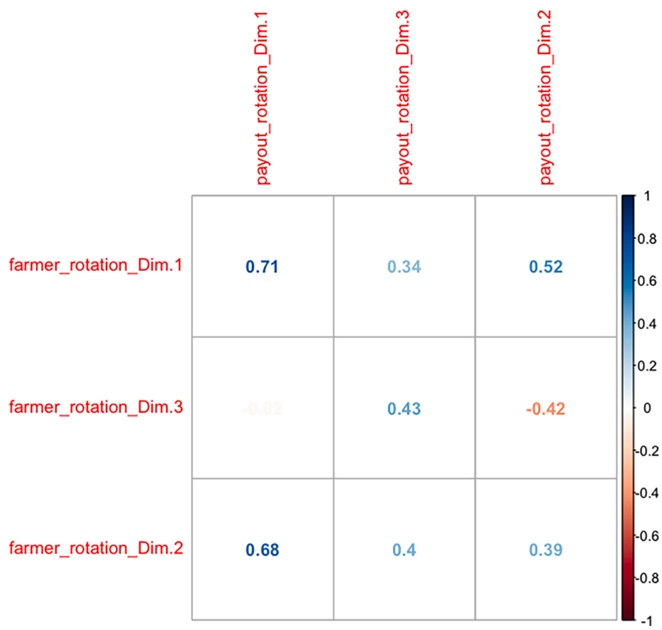

Fig. E1. Cross-correlation of coordinates for first 3 PCs.

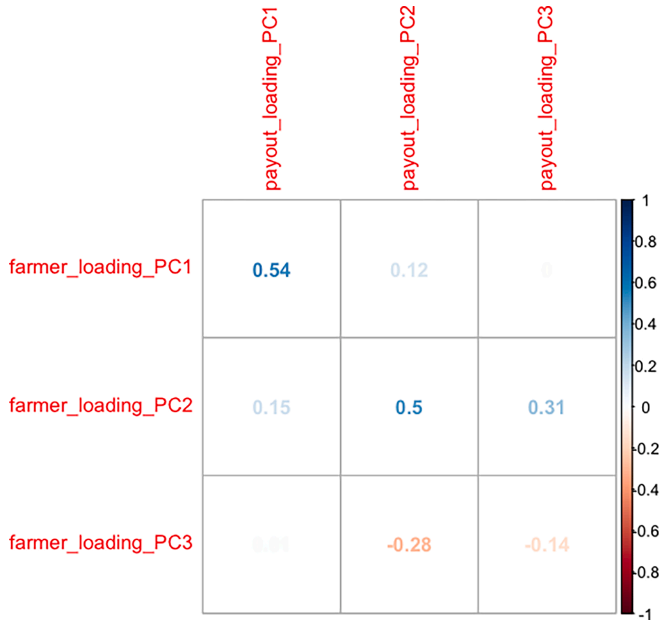

Fig. E2. Cross-correlation of loadings for first 3 PCs.

F. H2 regression auxiliary material

F.1 Panel vs fixed effect model diagnostic

Hausman Test.
data: yield ~ payout + as.numeric(year).
chisq = 0.25684, df = 2, p-value = 0.8795.
alternative hypothesis: one model is inconsistent.

F.2 Test for unit roots in yield

Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts).
data: yield ~ 1.
Wtbar = -9.4618, p-value < 2.2e-16.
alternative hypothesis: stationarity.

F.3 Yield autocorrelation plot

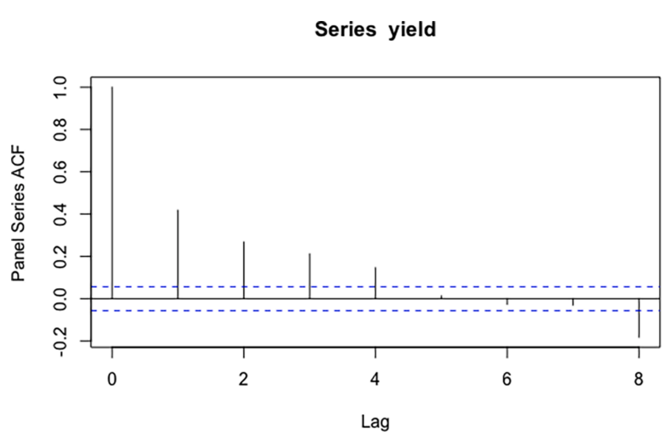

Fig. F1. Plot of district-level yield autocorrelation function.

Data availability

All of the data and code necessary to replicate the results of this paper is available on the project Github repository. Please note that for privacy purposes, the original village-level farmer focus group data is not included in this public repository. Instead, we only share the district-level aggregate data.

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