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Investigating the relationship between growing season quality and childbearing goals

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ABSTRACT

Agricultural production and household food security are hypothesized to play a critical role connecting climate change to downstream effects on women's health, especially in communities dependent on rainfed agriculture. Seasonal variability in agriculture strains food and income resources and makes it a challenging time for households to manage a pregnancy or afford a new child. Yet, there are few direct assessments of the role locally varying agricultural quality plays on women's health, especially reproductive health. In this paper we build on and integrate ideas from past studies focused on climate change and growing season quality in low-income countries with those on reproductive health to examine how variation in local seasonal agricultural quality relates to childbearing goals and family planning use in three countries in sub-Saharan Africa: Burkina Faso, Kenya, and Uganda. We use rich, spatially referenced data from the Performance Monitoring for Action (PMA) individual surveys with detailed information on childbearing preferences and family planning decisions. Building on recent advances in remote monitoring of seasonal agriculture, we construct multiple vegetation measures capturing different dimensions of growing season conditions across varying time frames. Results for the Kenya sample indicate that if the recent growing season is better a woman is more likely to want a child in the future. In Uganda, when the growing season conditions are better, women prefer to shorten the time until their next birth and are also more likely to discontinue using family planning. Additional analyses reveal the importance of education and birth spacing in moderating these findings. Overall, our findings suggest that, in some settings, women strategically respond to growing season conditions by adjusting fertility aspirations or family planning use. This study also highlights the importance of operationalizing agriculture in nuanced ways that align with women's lives to better understand how women are impacted by and respond to seasonal climate conditions.

1. Introduction

Poor women living in poor, agriculturally dependent countries face unique challenges associated with climate change. A growing body of empirical literature examines climate impacts on women's lives with a particular focus on reproductive and child health outcomes using spatially referenced population survey data combined with highly detailed climate and vegetation data (Bakhtsiyarava et al., 2018; Cooper et al., 2019a; Cooper et al., 2019b; Davenport et al., 2020; Dimitrova, 2021; Eissler et al., 2019; Sellers and Gray, 2019; Thiede and Gray, 2020).

Of the studies that specifically examine issues related to reproductive health and fertility, the focus is generally on the impact of extreme or anomalous temperature or precipitation events on pregnancy outcomes like preterm birth, low-birthweight, and miscarriage (Davenport et al., 2020), fertility goals or family planning behavior (Eissler et al., 2019; Sellers and Gray, 2019), and pregnancies (Barreca et al., 2018; Barreca and Schaller, 2020). This growing literature conceptually maps out the mechanisms linking climate change to women's lives usually by examining how temperature and precipitation anomalies (e.g., z-scores) can impact fertility behaviors and outcomes.

Although results are inconsistent and somewhat inconclusive, the existing evidence shows that one of the most important channels connecting climate and fertility in low income countries, operates through

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agricultural production and the consequent impacts on household food security and associated labor demands or health shocks (Eissler et al., 2019; Sellers and Gray, 2019). Despite this growing empirical attention to climate change impacts on fertility and the unique importance of agricultural production, there are only a few recent direct assessments of the role local agricultural production plays on fertility and reproductive health (Alam and Pörtner, 2018; Grace, 2017; Panter-Brick, 1996; Sasson and Weinreb, 2017). As climate change brings more variable temperature and precipitation, loss of arable land, and variable and inconsistent local seasonal agricultural productivity, it is important to improve our understanding of how experiencing environmental shocks affects individual-level outcomes and preferences, with a particular emphasis on the unique needs of women in these settings (Lau et al., 2021; Rao et al., 2019).

In this paper we build on and integrate ideas from past studies focused on climate change and growing season quality in low-income countries with those on reproductive health to examine how variation in local growing season quality relates to fertility goals and family planning use in three countries in sub-Saharan Africa: Burkina Faso, Kenya, and Uganda. We use rich, spatially referenced data from the Performance Monitoring for Action (PMA) household surveys with detailed information on individual-level fertility goals and the timing of family planning decisions. We include measures of growing season conditions across different time frames using fine-scale remotely sensed data, to better understand the fertility decision making process as it relates to dynamic growing season conditions. Finally, we examine heterogeneous effects by individual-level characteristics to expand scientific and policy understanding of family planning needs in a context of climate variability and food insecurity. With an explicit empirical focus on the agricultural-fertility pathway and attention to locally relevant measures of seasonal production, this research expands the small but growing literature focusing on the specific impacts of climate and agricultural variability on women's lives (Lama et al., 2020; Lau et al., 2021).

2. Background

2.1. Community-level growing season quality

Food security researchers continue to work to understand the impacts of climate change on seasonal food production and the resulting impacts on individual- and community-level food security (Brown et al., 2020). For example, within this area of research, results suggest that changes to the start of the growing season and the intensity and variability of rainfall at key time periods during the primary growing season are potentially important weather features that can indicate impending food shortages and food insecurity (Brown and de Beurs, 2008; Davenport et al., 2021; Husak et al., 2013; Shukla et al., 2021). Much of this research also increasingly incorporates farmer or local perceptions of growing season quality to better understand how community-members themselves perceive and respond to an impending poor harvest season and consequent food security (Ayanlade et al., 2017; Osgood et al., 2018; Ovuka and Lindqvist, 2000). Although food insecurity in subsistence farming settings often occurs chronically and seasonally, during the hunger season – the period when a household has depleted food stores from the past year's harvest but is not yet ready to harvest for the current year – the severity of the hunger season can vary based on the quality of the preceding year's production (Becquey et al., 2012; Handa and Mlay, 2006; Hill et al., 2019; Jiggins, 1986; Vaitla et al., 2009). Even for households that are not directly engaged in agricultural production, a poor growing season can mark a general shortage of locally available food staples and higher prices and fewer wage earning opportunities (Blackmore, 2021; Vaitla et al., 2009).

This body of literature has identified a range of different coping strategies. For example, households may strategically ration their food resources across individual members, they may sell livestock or other household goods, they may reduce household expenses associated with schooling, and they may also lean on family networks for financial support (Alam and Pörtner, 2018; Hill et al., 2019; Randell and Gray, 2019). In some settings, domestic organization of kin-networks, households, and communities shifts according to seasonal and resource needs. Family networks (which may include multiple generations and multiple households) may strategically send some individuals to urban areas for seasonal work during periods where there are fewer labor demands (Findley, 1994; Hampshire, 2006; Hertrich and Lesclingand, 2012).

These seasonal changes in agricultural conditions and household adaptation strategies have implications for childbearing outcomes and goals (Alam and Pörtner, 2018; Grace, 2017; Grace et al., 2017; Jiggins, 1986). One potential channel is through household labor needs. During harvest periods, labor demands may be highest, while the hunger season is also at its most severe resulting in nutritional deficiencies (Hill et al., 2019; Vaitla et al., 2009). Women may wish to avoid pregnancies or breastfeeding during this time or spend more time apart from partners due to differing household and agricultural responsibilities (Panter-Brick, 1996; Randell et al., 2021). Additionally, a bad growing season could result in more seasonal migration for work opportunities, which in turn delays sexual activity and conception (Eissler et al., 2019; Panter-Brick, 1996; Sellers and Gray, 2019). Seasonal agricultural production also influences household-level resources, which in turn may affect preferences around ideal family size. A particularly good growing season may change perceptions about the future and increase desired family size, since a larger family could be financially supported (Eissler et al., 2019; Sasson and Weinreb, 2017). In contrast, a bad growing season may affect resources available for health care (Hill et al., 2019) possibly resulting in families avoiding pregnancies to reduce prenatal care and delivery costs.

Although understudied, it is also possible that other aspects of domestic organization and planning, including reproductive health behaviors and childbearing goals, may also be modified to optimize household resources while achieving goals (Hampshire, 2006). Thus, choices around timing pregnancies may be part of an explicit household adaptation strategy in response to changing agricultural conditions and resource availability. While it is often assumed that women and couples strategically time pregnancies around individual/household needs in high-income settings (Sobotka et al., 2011; Van Bavel, 2010; Van Bavel and Klesment, 2017), much less attention has been given to changing childbearing goals and timing as an outcome of resource insecurity in low-income countries. Many questions remain as to the actual drivers underlying the relationship between fertility, food security and agricultural production in developing country settings, and in particular questions around childbearing goals, timing, and contraceptive use.

2.2. Fertility goals and family planning use

Research on women's fertility is vast and complex. A major theme in this area of research is contraceptive use and access as well as childbearing preferences, goals, and aspirations (Bongaarts, 2011; Choi et al., 2016; Ross and Stover, 2013; Trinitapoli and Yeatman, 2018). While spatially oriented and community-level studies do exist (Brauner-Otto et al., 2007; Yao et al., 2012), attention to community-relevant seasonal agricultural variation as it relates to contraceptive use or childbearing goals is uncommon (Grace, 2017). Other aspects of fertility research, including studies set in high income countries, are more commonly evaluated with a seasonal lens, namely those aspects related to conception and pregnancy/birth timing (Barreca et al., 2018; Dorélien, 2016; Lam and Miron, 1991). From this research, results suggest that births occur following a seasonal pattern, which indicates that there are either behaviors (e.g., sexual behavior) or aspects of biology (e.g., semen quality) that respond to seasonal characteristics and influence births. The linkages between food insecurity and energetic demands (sometimes more intense during repeated hunger seasons) was addressed by demographers in the 1980 s and 1990 s with a focus on nutritional impacts on fecundity and fertility in small, rural communities (Bongaarts, 1980; Mosher, 1979; Panter-Brick, 1996) where the transition from high to low fertility was often in its nascent stages and "modern" methods of family planning were not used. The results from this literature show that in some cases—when women lose weight during the period of intense agricultural labor demands—fecundity may be reduced in the short-term (Panter-Brick, 1996). Additionally, researchers noted how considering the timing of the growing season was an important aspect of the timing of childbearing (Mosher, 1979). While the emphasis on nutrition implies a direct relationship with food security and agricultural production, this research rarely linked seasonally varying environmental conditions to seasonal fertility and certainly was not conducted with large samples across a range of countries (Grace and Nagle, 2015).

More recently, larger scale research by Eissler and colleagues (2019) and Sellers and Gray (2019) suggests the potential for contraceptive use and childbearing goals to be influenced or impacted by local environmental conditions. Each study carefully outlines a range of potential mechanisms that might connect environmental variability with variation in reproductive health outcomes, goals, and contraceptive use. Echoing and synthesizing related scholarship, their linkages feature both behavioral and biological mechanisms that might underlie a climate - reproductive health connection. Notably, Eissler and colleagues explicitly focus on fertility goals (rather than specific health outcomes) and build on the work of Trinitapoli and Yeatman (2018) to include in their framework the potential for insecurity and variability in conditions to modify individual fertility goals and contraceptive behaviors. Fertility preferences and contraceptive use are crucial determinants of fertility outcomes, yet individuals may not be able to attain desired outcomes due to a variety of factors, such as access, availability, and affordability of contraceptives (Trinitapoli and Yeatman, 2018). While other research on contraceptive use behaviors has also examined the ways insecurity in conditions may shift how women incorporate contraception into their lives (Bledsoe et al., 1998), explicitly considering food and agricultural insecurity with regard to reproductive health goals is uncommon (Grace, 2017).

Here, we advance the research of contraceptive use and fertility goals and seasonal environmental influences on women's lives and health. We expand the existing research by merging health data with established, fine-scale remotely sensed proxy measures of agricultural production, with the use of growing season calendars, to develop locally relevant measures of growing season quality for each community. Thus, we are able to more directly evaluate the impact of growing season quality and at a community-relevant spatial scale (as opposed to coarser climate data). Additionally, we explicitly evaluate the impact of the two most recent growing seasons to help illuminate the relevant exposure windows that may influence behaviors and goals. Finally, our analysis assesses several dimensions of fertility preferences and contraceptive use to provide a nuanced perspective on changing goals and behaviors.

3. Study setting

We focus on three sub-Saharan African countries: Burkina Faso, Kenya, and Uganda. These countries have important commonalities relevant to this analysis – food insecurity is high and linked to annual and seasonal weather variations, as around 70% of the population is dependent on food and income derived from rainfed agriculture (FAO's Food and Agriculture Policy Decision Analysis (FADPA), 2015a, 2014). However, in each country, there is significant subnational variation in exposure to food insecurity linked to spatially varying rainfall patterns, infrastructure, and development. In Kenya and Uganda, for example, while much of the population resides in communities with relatively high levels of consistent rainfall, a substantial portion of the population lives in more marginal farming areas with increasingly inconsistent rainfall. For Burkina Faso, which is in the Sahel, where the climate and topography are significantly different from Kenya and Uganda, farmers consistently and reliably produce more agriculture than other areas within the country. These different growing and producing conditions are often associated with varying food insecurity risks and vulnerabilities.

In Burkina Faso, the growing season runs from mid-May to October and the primary harvest begins in September (Famine Early Warning Systems Network, 2021a). Kenya and Uganda are characterized by subnational differences in growing seasons. In Kenya, the eastern and northern regions have a short rainy (growing) season, as well as a longer growing season from mid-March to June, while the western and Rift Valley regions have a single, long growing season that spans mid-February to mid-August (Famine Early Warning Systems Network, 2021b). In Uganda, the majority of the country is described as bimodal, with the first growing season running from March to June and a second (shorter) season that begins in mid-August and lasts until December. In the Karamoja region of Uganda, which is in the northeast, a single growing season spans April to October (Famine Early Warning Systems Network, 2021c). Our analysis will leverage this spatial variation in the timing of growing seasons and local differences in the quality of seasonal agricultural production. Table 1 summarizes the growing seasons for each country included in this study.

4. Data & measures

4.1. Fertility intentions and family planning use

To conduct this analysis, we use IPUMS PMA data from Burkina Faso, Kenya, and Uganda from the 2016, 2017 and 2018 survey rounds for which GPS data are available (see Table 2). IPUMS PMA is the integrated version of the Performance Monitoring for Action data. These surveys contain highly detailed information on women's contraceptive use (type and timing) as well as pregnancies, pregnancy intentions and desired family size. The recall questions regarding family planning use allow us to construct a retrospective picture of contraceptive use for the 12 months prior to each woman's interview. The PMA data used in this analysis include displaced GPS latitude and longitude coordinates for the geographic centroid of each of the primary sampling units (enumeration area, or EA) sampled in select survey rounds. In contrast to the widely used Demographic and Health Surveys, PMA surveys

Table 1
Growing season timing and PMA surveys by country.

Country	Region	Growing (Rainy) Season	PMA Survey Waves & Interview timing
Burkina Faso	Entire Country	May-Oct	2017: Nov 2017-Jan 2018
			2018: Dec 2018 - Jan 2019
Kenya	West & Rift Valley	Mid-Feb - mid-Aug	2016: Nov-Dec
	East & North	Mid-Oct - mid-Dec	2017: Nov-Dec
	East & North	Mid-Mar - mid-June (longer season)	2018: Dec 2018 - Jan 2019
Uganda	Karamoja	Apr - Sep	2017: Apr-Jun
	Rest of country	Mar - Jun (first season)	2018: Apr-Jun
	Rest of country	Mid-Aug - Nov (second season)	

Notes: Growing season calendars are from the Famine Early Warning Systems Network (https://fews.net/). For Uganda and Kenya, where different regions have different growing seasons, we identify which region the PMA enumeration area centroid falls into and use the primary or longest growing season for the analysis.

Table 2
Summary statistics of outcomes, NDVI variables, and control variables.

	Burkina Faso	Kenya Sample	Uganda
Outcomes			
Wants children, % (n)	67% (3,326)	55% (5,098)	79% (3,495)
Preferred time to wait before next child (months), Mean (SD)	39 (24)	41 (31)	38 (24)
Started a methos of family planning, % (n)	21% (1,106)	18% (1,872)	17% (798)
Discontinued family planning, % (n)	10% (528)	6.8% (700)	6.6% (310)
Growing Season Quality			
Subseasonal Max NDVI, Mean (SD)	0.27 (0.10)	0.58 (0.12)	0.62 (0.11)
Full Season Max NDVI, Mean (SD)	0.50 (0.12)	0.69 (0.11)	0.69 (0.10)
Control Variables			
Age, Mean (SD)	30 (8)	32 (8)	31 (9)
Children born, % (n)			
0	7.5% (395)	5.2% (532)	7.2% (338)
1	16% (824)	17% (1,713)	17% (788)
2	17% (882)	21% (2,142)	17% (798)
3	14% (717)	19% (1,972)	15% (706)
4	12% (617)	14% (1,388)	13% (602)
5+	35% (1,842)	24% (2,476)	31% (1,482)
Months since last birth, Mean (SD)	39 (46)	59 (56)	45 (48)
Household size, Mean (SD)	5.6 (2.8)	5.3 (2.4)	7.5 (4.5)
Education level, % (n)			
Primary or less	73% (3,838)	59% (6,023)	83% (3,903)
More than primary	27% (1,437)	41% (4,213)	17% (810)
Wealth tercile, % (n)			
Lowest tercile	41% (2,175)	34% (3,522)	31% (1,483)
Middle tercile	30% (1,606)	33% (3,371)	28% (1,314)
Highest tercile	28% (1,496)	33% (3,337)	41% (1,916)
Observations			
Number of Women	5,278	10,236	4,715
Number of EAs	110	151	83

Notes: Outcomes and control variables are derived from PMA survey questions. NDVI variables are derived from NASA's MODIS/Terra Vegetation Indices Monthly L3 Global 0.05 Deg CMG V061 product.

countries every year and resamples the same EAs in each survey round;[1] thus, the data are longitudinal at the EA-level, allowing us to observe the same EA under different agricultural conditions, which is central to our fixed effects econometric strategy. The GPS points were displaced up to 2 km for urban areas and up to 5 km for rural areas, with 1% of rural EAs displaced up to 10 km. However, these data allow us to associate vegetation index data (see Growing Season Quality section below) with women in these samples with reasonable accuracy. Fig. 1 maps the EA centroids in all three countries and Table 1 lists the survey waves and timing of interviews for each country. As can be seen in Fig. 1, the enumeration areas sampled in Kenya are primarily from the south-western region of the country, therefore we refer to the *Kenya sample* throughout this analysis.

Dependent Variables: Because measuring fertility and childbearing preferences is complex (e.g., Trinitapoli and Yeatman, 2018), we construct four dependent variables from the PMA data that reflect different dimensions of fertility intentions and family planning use: 1) fertility preferences, 2) preferred time before having another child, 3) starting family planning, and 4) stopping family planning. The fertility preferences outcome is derived from a survey question that asks "Would you like to have a/another child or would you prefer not to have any / any more children?" and is coded as a binary variable that takes a value of "1" if the respondent indicated they wanted any or more children. The question about preferred time before having another child was only asked of respondents who indicated they wanted a child in the future and is recorded in months. These first two outcomes are measured at the time of interview.

For outcomes 3 and 4 - the two contraceptive use outcomes, we use the detailed information on timing of family planning choices to identify whether each respondent started or stopped a method of family planning in the 12 months prior to the interview. Because of the level of detail collected on family planning use, respondents can both start and stop a method of family planning within the one-year time period considered; thus, these two outcomes are not mutually exclusive. Our analytic sample is restricted to respondents of reproductive age who are married or in a union, as the data indicates that pregnancies out of union are not very common and out marriage pregnancies are typically unwanted (Ameyaw et al., 2019) and remain taboo in much of sub-Saharan Africa (Smith-Greenaway, 2016).[2] We also excluded any women who were unable to conceive (ie., women who reported using sterilization as a form of family planning, which included 185 respondents in total across all three countries). The initial raw sample contained 32,999 observations across all three countries (6,844 in Burkina Faso, 17,606 in the Kenya sample, and 8,449 in Uganda), after eliminating women who could not become pregnant and restricting to only married women, the final analytic sample included 20,299 women (see Table 2 for a country-specific breakdown).

Control Variables: We include a selection of control variables that are well-known to impact fertility preferences and outcomes: age, parity (number of children ever born), household size, respondent's level of education, and household wealth tercile (e.g., Eissler, Thiede, and Strube 2019).

Table 2 presents summary statistics for the primary outcomes and control variables derived from the PMA data, separately for each country. A majority of respondents desire children in the future, ranging from 55% in the Kenya sample to 79% in Uganda. However, of these respondents many would like to wait a substantial amount of time before their next child, as the average time preferred to wait before the next child is more than three years in all countries. These data also indicate that women are using family planning to control and time their desired fertility, with almost 20% of each sample starting a method and between 6 and 10% discontinuing a method in the 12 months prior to the interview. Note that these measures do not capture overall contraceptive prevalence, because they are constructed to identify changes in family planning use. Thus, anyone who consistently used/did not use a method of family planning in the year preceding the PMA interview would appear here as neither starting nor discontinuing family planning.

4.2. Growing season quality

We utilize a remotely sensed based measure of vegetation health, the Normalized Difference Vegetation Index (NDVI) as a proxy for community-level food production and availability. The connection between NDVI variability and agricultural production has been consistently demonstrated over the past forty years (Bartholome, 1988;

[1] PMA does however refresh their samples periodically, so all surveys waves for a given country are not necessarily the same EAs. In our analysis, we only use survey rounds where the EA is sampled at least twice. Refer https://www.pmadata.org for more details on the sampling strategy by country and round.

[2] Across the three countries in our sample<6% (Burkina Faso), 16% (Kenya), and 11% (Uganda) of pregnancies occur out of marriage/union.

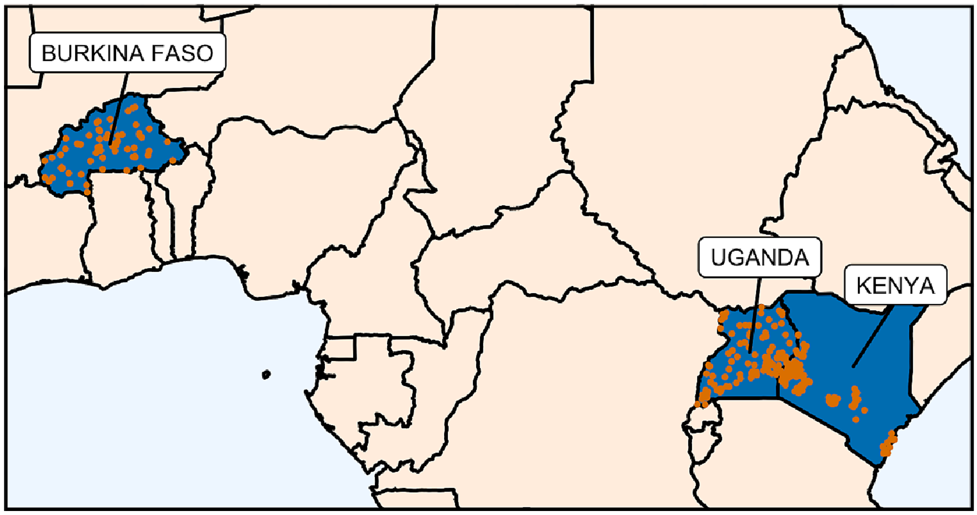

Fig. 1. Map of PMA enumeration area (EA) centroids in Burkina Faso, Kenya, and Uganda. The displaced GPS latitude and longitude coordinates for the geographic centroid of the sampled EAs in each country are shown in orange. Note that the PMA Kenya survey sampled EAs primarily from the southwest region of the country. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Battude et al., 2016; Brown et al., 2014; Rasmussen, 1998, 1997; Vrieling et al., 2008). NDVI is a commonly used measure for monitoring seasonal quality and is used by international humanitarian agencies for early warning systems focused on food aid targeting (Brown et al., 2008; Brown and de Beurs, 2008; Stige et al., 2006; Vrieling et al., 2008). NDVI also has the advantage of being comparable across regions, consistently measured, and available over a long-time period. Using NDVI as a proxy for seasonal agricultural quality allows for researchers to be 1) more policy relevant through the use of a common measurement approach, and 2) address food security research questions in data poor regions without any time-varying information about smallholder farmer practices and local food availability.

We use NDVI data from NASA's MODIS/Terra Vegetation Indices Monthly L3 Global 0.05 Deg CMG V061 product, available from 2000 to the present (Huete et al., 1994). This provides a monthly composite vegetation measure with a spatial resolution of 0.05 degrees (approximately 5 km). This data allows us to measure growing season conditions at the PMA sampling cluster locations across time, within the season, and measure the spatial variability in relative growing season conditions.

We begin by extracting monthly NDVI values for the grid-cell that each enumeration area falls into, according to the longitude and latitude of the EA centroid provided by PMA. Because the majority of EAs are displaced by up to 5 km, extracting the grid-cell that each EA falls into will capture the true location the majority of the time. Because 1% of rural EAs are displaced by up to 10 km, we calculate NDVI measures based on a 10 km buffer circle around each EA and use this measure in a sensitivity analysis. Following the growing season calendars produced by FEWSNET, we identify when the primary growing season occurs in each country or region.[3] We then calculate two primary growing season quality measures for each enumeration area: 1) the subseasonal maximum NDVI based on the first two months of the growing season, and 2) the maximum NDVI from the full growing season.

The subseasonal NDVI measure additionally allows us to identify whether and how individuals respond to early signals of growing season quality (as captured by vegetation indices). Recent work has shown that in agriculturally dependent regions in Africa, delayed onset of rain and rainfall conditions in the early months of the growing season are related to the probability of agricultural drought, and hence chances of local food insecurity (Brown and de Beurs, 2008; Davenport et al., 2021; Husak et al., 2013; Shukla et al., 2021). Relatedly, research investigating linkages between farmer perceptions and seasonal quality also indicates the importance of early season conditions in shaping farmer perception of season quality. This research suggests that farmers may gauge season quality and plan accordingly based on sub-seasonal conditions (see, for example, Ovuka and Lindqvist (2000) and Ayanlade et al. (2017)). Relevant to our analysis, in the Indonesian context delayed onset of the monsoon was associated with fertility intentions (Sellers and Gray 2019). Thus, application of the maximum NDVI during the first two month provides us an opportunity to identify an earlier warning indicator of the food insecurity (than the maximum NDVI over the full growing season) which may have impacts on the fertility preferences later in the season or post season.

Key Independent Variables: Ex-ante it is unclear whether the most recent growing season or the previous year's growing season will have the biggest impact on fertility aspirations and family planning decisions. To explore the differential impact of different years' growing seasons, we calculate a lagged value of the subseasonal and full season NDVI measures. Thus, we have four sets of NDVI measures: 1) subseasonal maximum NDVI in year *t* (the interview year), 2) subseasonal maximum NDVI in year *t-1* (the year prior to the interview year), 3) full season maximum NDVI in year *t*, and 4) full season maximum NDVI in year *t-1*. While older years' growing seasons could be relevant (e.g., *t*-2 or *t*-3) or also cumulative effects, given the lack of full birth histories and migration information in the PMA, as a conservative approach we restrict the analysis to look only at the current and previous year to rule out contamination and bias. For example, since we do not know how long women have lived in their current residence, we would introduce bias when matching individuals to community-level growing season data that they may not have experienced if they did not live in that community three or four years prior to the interview. And, since we lack a full birth history, we would not know about births that occurred in previous years, which bias any assessment of fertility preferences and behavior.

We merge the NDVI measures with the PMA data according to the enumeration area and year, resulting in both spatial and temporal variation in NDVI. Summary statistics of the NDVI-derived growing season variables are presented in Table 2 and the variation in EA-level subseasonal max NDVI across years is shown in Fig. 2. The subseasonal and full season NDVI maxima are used in the primary analysis,

[3] In the case of Uganda and the Kenya sample, where regions vary in growing season timing and experience multiple growing seasons (Table 1), we use the primary/longest growing season (Famine Early Warning Systems Network 2021c, [b] 2021).

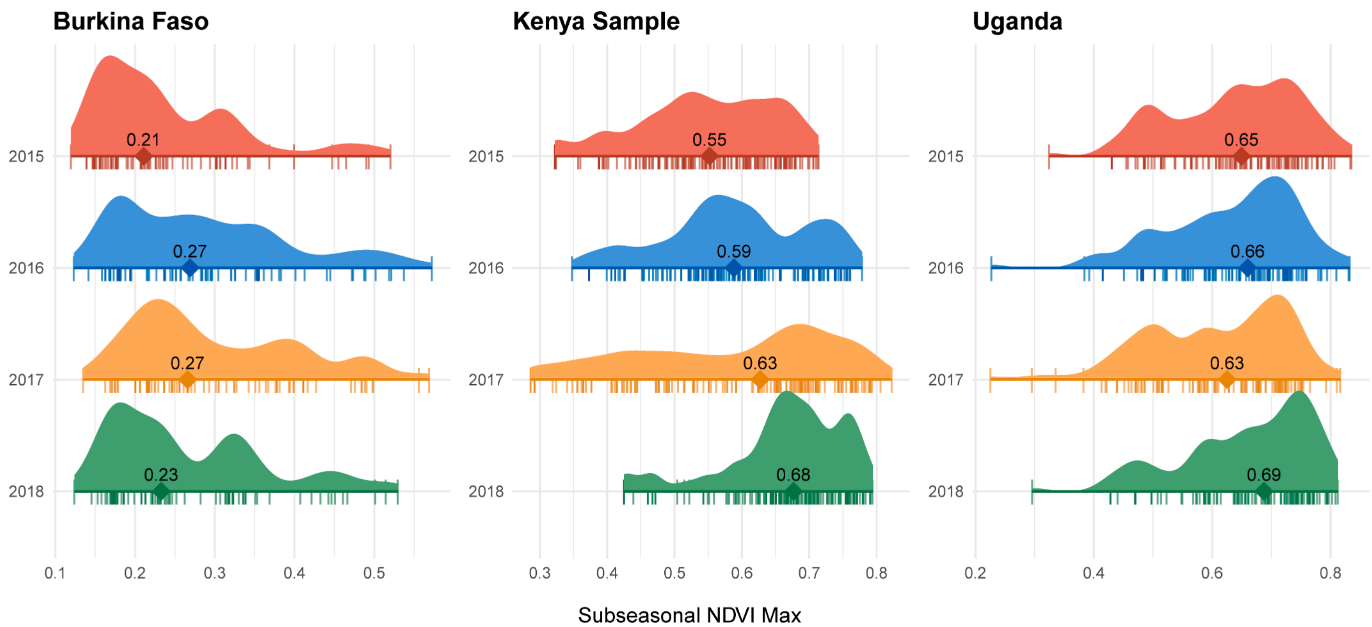

Fig. 2. Variation in subseasonal NDVI maxima by country and year. Each vertical bar represents the subseasonal NDVI maximum for a given EA. The diamonds on each plot indicate the median value across all EAs in a given year (with the median value printed above the diamond). The shaded regions represent density plots of the subseasonal NDVI maxima for each country and year. This figure shows substantial variation both within and across countries and years of the subseasonal NDVI maxima.

however we also calculated an NDVI z-score that calculates the deviation of the maxima from a 5-year growing season average within each EA, which is used for a sensitivity analysis presented in the Appendix.

5. Empirical strategy

Our analysis has three objectives: (1) examine the relationship between growing season quality and reproductive health outcomes for women in three different sub-Saharan African countries, (2) empirically assess which windows of exposure matter (e.g., current versus past growing seasons), and (3) examine how these relationships vary by individual-level characteristics, such as education, wealth, and time since most recent birth. We leverage differences in the timing of PMA interviews, as well as the spatial and temporal variation in growing season quality across enumeration areas both within and across each of the three countries. Crucially, because the PMA re-sampled the same enumeration areas in these countries, our data constitutes a panel of EAs (with different cross-sections of women interviewed in each wave), allowing us to observe the same EA under different conditions in different years. To conduct this analysis, we use ordinary least squares (OLS) regression to estimate a series of linear regression models that follow Equation (1):

$$Y_{iet} = \beta NDVI_{et} + \lambda X_{iet} + \gamma_e + \mu_t + \delta_{m(t)} + \epsilon_{iet} \quad (1)$$

where Y_{iet} represents one of the four outcomes for woman i in enumeration area e in survey year t, $NDVI_{et}$ represents one of the NDVI measures defined above for enumeration area e in year t, and X_{iet} is a vector of individual-level controls including age, education, parity, time since last birth, and household wealth. The coefficient on NDVI (β) is the parameter of interest and captures the relationship between growing season quality and each outcome. In the case of the three binary dependent variables, the coefficient should be interpreted as a change in the probability of the outcome occurring. To account for unobserved, EA-level differences that may be correlated with reproductive health, we include EA fixed effects (γ_e), which means we are comparing outcomes for women who live in the same EA but experience different growing season conditions across time. Because the data includes multiple PMA survey rounds conducted over several years for each country, we include a year fixed effect (μ_t) that controls for any year-specific effects that are common across each country. Finally, to account for seasonal variation that is unrelated to growing seasons and any systematic correlation between the timing of surveys and the growing season, we include an interview month fixed effect ($\delta_{m(t)}$). Analyses are conducted separately for each country and survey weights are not used because we are using a distinct subset of the original sample for which the weights were designed. To adjust for within group homogeneity we cluster standard errors by the enumeration area (Solon et al., 2015).

To understand how the effect of growing season quality is moderated by individual-level factors associated with fertility behaviors and goals, we run a series of heterogeneity analyses. To do this, we interact the NDVI variable in Equation (1) with indicators for educational attainment and birth spacing. To examine heterogeneity by birth spacing we categorize women according to whether it has been less than one year since their last birth, more than one year since their last birth, or they have not given birth to any children.

We also conduct a series of supplemental analyses and robustness tests, including estimating a version of Equation (1) without EA fixed effects, as well as a pooled version estimated on combined data from all three countries where we replace the year fixed effect in Equation (1) with a country-by-year fixed effect, which helps to account for time trends that impact the outcomes and are constant within a country but differ across countries. As mentioned above, we conduct several sensitivity analyses around the NDVI data, running models that use (1) 10 km buffers to calculate growing season variables and (2) NDVI z-scores instead of maxima, which are presented in the Appendix.

6. Results

6.1. Country specific results

Fig. 3 presents regression results for the country-specific models for all four outcomes estimated using Equation (1) (for regression tables see Tables A.1 – A.12 in the Appendix). In each panel, the coefficient on NDVI (β from Equation (1) is plotted as the dot and the vertical lines represent the 95% confidence interval around the point estimate. The

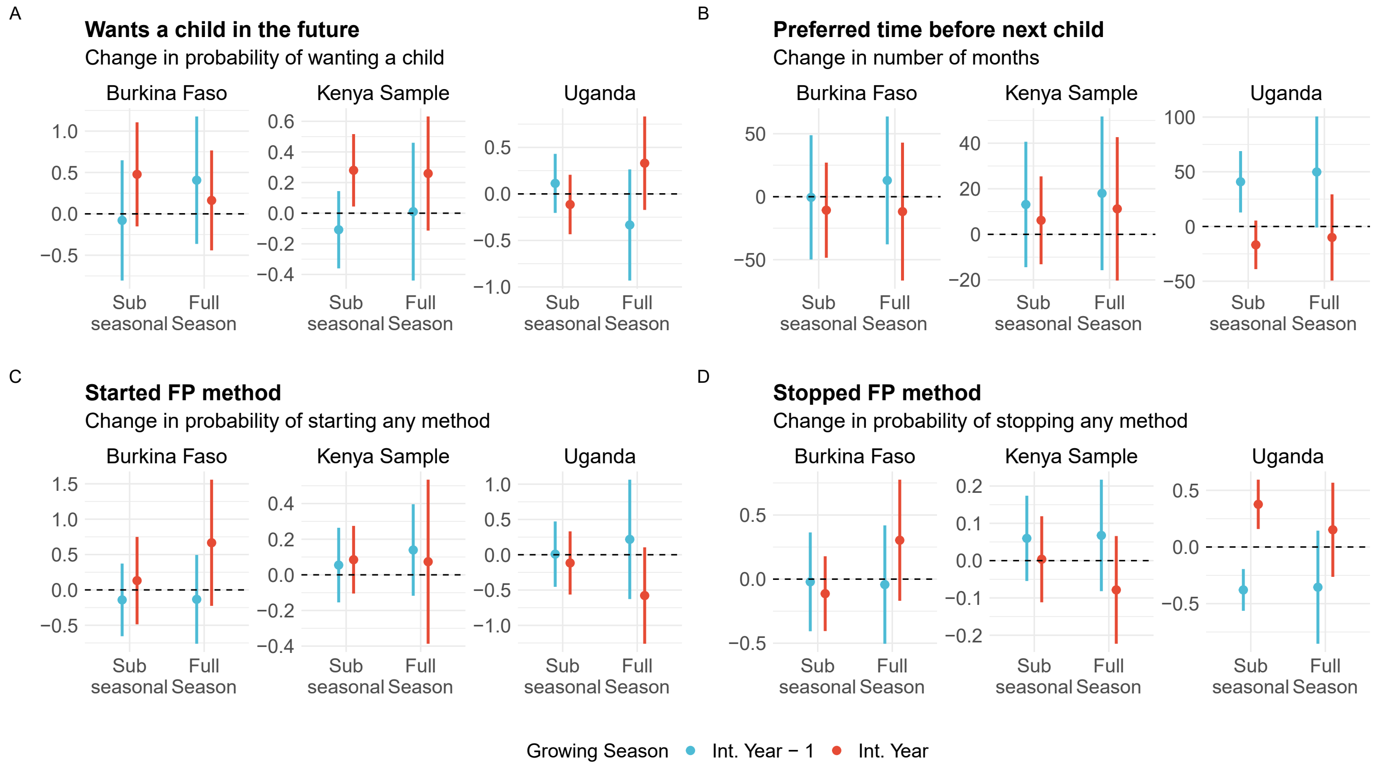

Fig. 3. Regression results for fertility preferences and family planning use by country. Each dot represents the coefficient on NDVI (β from Equation (1) and the vertical lines are 95% confidence intervals. All models are estimated with enumeration area fixed effects, year fixed effects, and interview month fixed effects. They control for age, parity, education, wealth, and household size. Standard errors are clustered by enumeration area. For each country, we show the results using the subseasonal growing season maximum NDVI on the left and the corresponding result for the full growing season on the right. Results using the growing season that immediately precedes the PMA interview are shown in red, while results for the lagged growing season (e.g., the year before the PMA interview) are shown in blue. The dependent variables for the models presented in Panel A, C, and D are binary and coefficients should be interpreted as percentage point changes in the probability of the outcome occurring. Panel B reports results for preferred time (in months) before having another child, thus the coefficients should be interpreted as the change in number of months. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dashed horizontal line marks 0 and any confidence interval that crosses this line indicates a statistically insignificant result at the 5% level. For each country, we show the results using the subseasonal growing season maximum NDVI on the left and the corresponding result for the full growing season on the right. Results using the growing season that immediately precedes the PMA interview (year *t*) are shown in red, while results for the lagged growing season (e.g., the year before the PMA interview, year *t-1*) are shown in blue.

6.2. *Desire for children in the future*

These results show that an increase in the maximum NDVI, or growing season quality, in the most recent growing season before the interview is positively associated with the probability of desiring a child in the future in some settings (Fig. 3A, Appendix Table A.1 and A.5). In the Kenya sample, the results imply that experiencing a better than average growing season is associated with a 28-percentage point increase, respectively, in the probability a woman wants another child, which is statistically significant at the 5% level. To put this magnitude in context, a one-standard deviation increase in the subseasonal NDVI (0.12) is associated with a 3.4-percentage point increase in the probability a woman wants another child. In all three countries the coefficients are larger with narrower confidence intervals when using the subseasonal measure relative to the full season measure. Additionally, growing season quality measured in the interview year appears to be more relevant than the year prior, as we do not observe a significant association between the lagged growing season fertility preferences in Burkina Faso and the Kenya sample.

6.3. *Preferred time to wait before having a child*

In Uganda, while growing season quality was not associated with fertility preferences, there is a significant relationship between NDVI and the preferred amount of time to wait before having a child (Fig. 3B, Appendix Table A.10). Specifically, a better than average season in the lagged season year is associated with a 41-month increase in the desired time to wait (significant at the 1% level), while a one-standard deviation increase in lagged growing season quality (equivalent to 0.09) implies a 3.7 month increase in the desired time before having another child. We see suggestive evidence for a decrease (approximately 16 months) in the desired time to wait associated with an increase in the maximum NDVI in the interview year, however this result is not significant at conventional levels.

6.4. *Initiating and discontinuing family planning*

This pattern is mirrored in the results for discontinuing family planning use among respondents in Uganda (Fig. 3D, Appendix Table A.12): a good growing season in the interview year is associated with a greater likelihood of discontinuing family planning, while women who experienced a good growing season in the previous year are less likely to discontinue their use of family planning (in the interview year), both results are statistically significant at the 1% level. The coefficient implies that an increase in the growing season quality in the interview year is associated with a 38-percentage point increase in the probability of discontinuing contraception. Put in terms of changes in NDVI that make be likely to occur in practice, a one standard deviation (0.11) increase in subseasonal NDVI in the interview year is associated a 4.2-percentage point increase in the probability of discontinuing family planning. In other words, experiencing a better growing season more recently means women want to accelerate their childbearing, but if they experienced a better than average growing season the year before, they want to wait longer before having a child. This seemingly odd pattern of results suggests that in the intervening year (the year between *t-1* and *t*), something moderates the relationship between growing season quality and fertility preferences. This motivates our investigation in the next section of whether having a child during that year can help explain this result.

We do not observe any statistically significant relationships between the probability of starting a method of family planning and growing season quality (Fig. 3C) in any of the three countries. In Burkina Faso there is a large, positive association when using the full season NDVI measure. In Uganda we find a large, negative association. In both cases, the confidence intervals are large and the results insignificant at conventional levels. The negative direction of the association for Uganda is consistent with the findings in Uganda for birth spacing and discontinuing family planning use (e.g., a good growing season is associated with waiting less time before having another child, lower probability of starting family planning, and higher probability of stopping family planning).

Overall, these country-specific results are similar to those estimated on a pooled version of the data that combines all three countries and includes country-by-year fixed effects (Appendix Fig B.1). We also assessed the sensitivity of these findings to two alternative NDVI measures: (1) subseasonal NDVI max (in the interview year) calculated in a 10 km buffer zone around each EA centroid and (2) a subseasonal NDVI z-score (in the interview year) calculated at the grid-cell level for each EA using a 5-year subseasonal growing season mean and standard deviation. We re-estimated Equation (1) using each of these alternative NDVI measures and plot the results for each country and outcome in Appendix Fig B.2. Both the 10 km buffer and z-score results are consistent with the primary subseasonal NDVI max results shown in Fig. 3.

The magnitudes are very similar for the 10 km buffer measurements, while the point estimates using the z-scores are much smaller, which is reasonable as the units are in standard deviations. Thus, the main findings are robust to using pooled data, 10 km buffers, or a subseasonal NDVI z-score. However, the results from models estimated without enumeration area fixed effects are often quite different from those estimated with the EA fixed effects (Appendix Tables A.1 – A.12). The purpose of the EA fixed effects is to control for unobserved, time invariant community-level factors that may impact reproductive health outcomes, and particularly may be correlated with the measure of growing season quality and bias the estimation. For example, community norms around providing support to households who experience economic hardship may influence childbearing preferences and be common within an EA. Therefore, our preferred specification includes the EA fixed effects.

6.5. Heterogeneity analysis

In this section, we explore the heterogeneity of the primary results by the education level of respondents and birth spacing. There may be a disconnect between fertility preferences and the ability to act on them (e.g., via starting or discontinuing contraceptives) due to various factors related to awareness, access, and affordability of reproductive health services. Additionally, differences in the primary results between the growing season conditions of the interview year and the year prior may be related to childbearing during the intervening year and the experience of having a young child at home. In the main results, the subseasonal NDVI measures were similar to those calculated from the full season but generally larger coefficients with smaller confidence intervals (Fig. 3). Therefore, for brevity we utilize only the subseasonal NDVI maximum calculated in the interview year for these heterogeneity analyses.

Table 3 presents the results of the interacted models, estimated separately for each country (in columns) and outcome (in Panels A-D). We present only the coefficients for NDVI, the main effects of each heterogeneity variable (education and birth spacing) and the corresponding interaction terms with the education and birth spacing variables. For each outcome, the coefficient on NDVI represents the effect of NDVI for the dropped category of the interaction term (e.g., less than primary education and having a child older than 1 year old) and the coefficient on the interaction represents the difference in the effect of NDVI by the included category (e.g., more than primary education, having a child under 1 year old, and having no children).

6.6. Heterogeneity by education

In Burkina Faso, while there was no detectable *average* relationship between growing season quality and preferred time to wait before having another child or probability of starting contraception, the heterogeneity analysis reveals the relationship varies by education. Specifically, for women with less than a primary school education an increase in NDVI is associated with a 14-month decrease in desired time to wait, although this relationship is imprecisely estimated. Relative to less educated women, for women who completed more than primary school an increase in growing season quality is associated with a desire to delay childbearing by 19 months (significant at the 10% level). Thus, the overall effect implies an increase growing season quality is associated with desire to delay childbearing by 5 months for more educated women, although the overall effect is not statistically significant.

The heterogeneity results in Burkina Faso for starting a method of family planning are consistent with these preferences to delay childbearing. For less educated women, there is no effect of NDVI (Table 3, Panel C, row 1), whereas for women who completed more than primary school an increase in growing season quality is associated with an additional 55-percentage point increase in the probability of starting contraceptives (significant at the 1% level) relative to women without a primary school education (the overall effect of 56 percentage points, which is calculated as the sum of the coefficient on NDVI and the interaction term, is significant at the 10% level).

For the other outcomes and countries, education does not moderate the effect of growing season quality. In other words, the effect of a good growing season is the same for more and less educated women.

6.7. Heterogeneity by birth spacing

In the final three columns of Table 3, we examine how the results are moderated by the amount of time since a woman's most recent birth, which we operationalize as having a child within the year prior to the PMA interview or whether the woman has no children. In these models, the coefficients for NDVI represent the effects of growing season quality for women whose last child was born more than one year before the interview and the interaction coefficients should be interpreted as relative to this population. The amount of time between having children moderates the relationship between growing season quality and fertility preferences (Panel A) preferred time to wait before having a child (Panel B) and starting a method of family planning (Panel C), but the relationship varies by country and outcome.

These results suggest that in the Kenya sample, among women who do not have very young children at home, an increase in subseasonal NDVI is associated with a 28-percentage point ($p < 0.05$) increase in the desire for children in the future, but this relationship is 35 percentage points larger ($p < 0.01$) for women without any children. Thus, the overall effect of a good growing season for women without children is quite large: one-unit increase in subseasonal NDVI is associated with a 63-percentage point increase the probability she wants a child in the future ($p < 0.001$). In terms of changes in NDVI that may be reasonably expected, experiencing a one-standard deviation (0.12) increase in

Table 3
Interaction models estimating the effect of growing season quality by education and birth spacing.

	Burkina Faso (1)	Kenya Sample (2)	Uganda (3)	Burkina Faso (1)	Kenya Sample (5)	Uganda (3)
Panel A: Wants a child in the future						
NDVI	0.45	0.28**	−0.09	0.55*	0.28**	−0.07
	(0.32)	(0.12)	(0.16)	(0.32)	(0.14)	(0.18)
More than primary school	−0.04	−0.00	0.11**	0.03*	0.06***	0.07***
	(0.04)	(0.05)	(0.05)	(0.01)	(0.01)	(0.01)
NDVI × More than primary school	0.11	−0.00	−0.14			
	(0.12)	(0.08)	(0.09)			
Child under 1 at home				0.01	−0.03	0.02
				(0.03)	(0.06)	(0.07)
No children born				0.08*	−0.06	−0.11*
				(0.04)	(0.08)	(0.07)
NDVI × Child under 1 at home				−0.10	−0.03	−0.02
				(0.10)	(0.09)	(0.11)
NDVI × No children born				−0.09	0.35***	0.22*
				(0.13)	(0.12)	(0.11)
Panel B: Preferred time before next child						
NDVI	−14.27	7.42	−16.52	−7.25	−0.94	−13.46
	(18.92)	(9.26)	(11.61)	(19.56)	(9.48)	(11.81)
More than primary school	−2.02	2.54	2.84	1.54	−1.86	0.68
	(3.90)	(6.32)	(6.35)	(1.69)	(1.16)	(1.21)
NDVI × More than primary school	18.62*	−4.01	−1.40			
	(10.65)	(10.10)	(10.53)			
Child under 1 at home				12.36***	−4.80	7.43
				(2.25)	(4.65)	(5.96)
No children born				−5.47	3.46	10.91
				(4.61)	(13.13)	(8.27)
NDVI × Child under 1 at home				−3.29	24.16***	−4.46
				(7.21)	(7.84)	(9.56)
NDVI × No children born				12.53	−0.61	−22.29*
				(15.81)	(17.30)	(12.96)
Panel C: Started FP method						
NDVI	0.01	0.11	−0.09	0.19	−0.01	−0.14
	(0.30)	(0.10)	(0.23)	(0.23)	(0.10)	(0.23)
More than primary school	−0.08*	0.10**	0.14	0.06***	0.03***	0.03**
	(0.04)	(0.04)	(0.09)	(0.01)	(0.01)	(0.01)
NDVI × More than primary school	0.55***	−0.09	−0.14			
	(0.15)	(0.06)	(0.14)			
Child under 1 at home				0.11**	0.00	−0.03
				(0.05)	(0.10)	(0.09)
No children born				−0.10**	−0.00	−0.05
				(0.04)	(0.08)	(0.10)
NDVI × Child under 1 at home				0.16	0.50***	0.20
				(0.16)	(0.16)	(0.15)
NDVI × No children born				−0.15	−0.12	−0.13
				(0.13)	(0.12)	(0.14)

(*continued on next page*)

Table 3 (*continued*)

	Burkina Faso (1)	Kenya Sample (2)	Uganda (3)	Burkina Faso (1)	Kenya Sample (5)	Uganda (3)
Panel D: Stopped FP method						
NDVI	−0.12	−0.01	0.38***	−0.13	0.02	0.38***
	(0.15)	(0.06)	(0.11)	(0.15)	(0.06)	(0.12)
More than primary school	−0.02	−0.03	0.01	−0.00	0.00	−0.00
	(0.03)	(0.03)	(0.06)	(0.01)	(0.01)	(0.01)
NDVI × More than primary school	0.03	0.04	−0.02			
	(0.11)	(0.05)	(0.10)			
Child under 1 at home				−0.04**	−0.04	−0.08
				(0.02)	(0.03)	(0.06)
No children born				0.01	−0.03	0.05
				(0.04)	(0.07)	(0.10)
NDVI × Child under 1 at home				−0.04	−0.04	−0.01
				(0.06)	(0.05)	(0.08)
NDVI × No children born				−0.09	0.10	−0.13
				(0.15)	(0.12)	(0.16)

Notes: ***: 0.01, **: 0.05, *: 0.1. Each column and panel represent an estimation of Equation (1), where NDVI is interacted with a different variable. The first three columns present results for interactions with education, the second three present results for interactions with an indicator for birth spacing (where women were classified according to whether it had been one or more years since their most recent birth or they have no children). Results for each of the four primary outcomes are reported in panels A (fertility preferences), B (preferred time before next child), C (starting a method of family planning), and D (discontinuing family planning use). All models are estimated with enumeration area fixed effects, year fixed effects, and interview month fixed effects. They control for age, parity (dropped in the birth spacing heterogeneity models due to collinearity), education (dropped in the education heterogeneity models due to collinearity), wealth, and household size. Standard errors are clustered by enumeration area.

subseasonal NDVI is associated with a 7.5-percentage point increase the probability she wants a child in the future. In contrast, for women with young children at home there is little difference in the effect of NDVI relative to women who have not given birth recently (a statistically insignificant 3-percentage point decrease). The overall effect of a good growing season for women with young children at home therefore suggests a 26-percentage point increase in the probability of wanting more children ($p < 0.10$).

In Uganda, on the other hand, there is a small negative and statistically insignificant relationship between growing season quality and desire for children in the future among women who have older children (-0.07, Table 3, Panel A, Column 6, Row 1). For women without children, this negative relationship is offset by a 22-percentage increase ($p < 0.10$) in the probability of desiring a child in the future. Taken together, for women without any children NDVI is associated with a 14-percentage point increase in the probability of desiring children in the future, however the total effect is not statistically significant.

In the Kenya sample and in Uganda, birth spacing also moderates the relationship between growing season quality and the amount of time women want to wait before having their next child. In both settings, there are relatively small, negative, and statistically insignificant associations for women without young children at home (Table 3, Panel B, Columns 5 and 6, Row 1). In the Kenya sample, this relationship is moderated by a desire to delay childbearing by 24 months ($p < 0.01$) for women with young children at home, while in Uganda the negative relationship is even more negative among women without any children who want to shorten the time before their next child by an additional 22 months ($p < 0.10$); these differences are both relative to women with older children at home (Table 3, Panel B, Columns 5 and 6, Row 1). The corresponding overall effect of NDVI in the Kenya sample for women with young children is a 24-month increase ($p < 0.05$) in preferred time to wait and in Uganda for women without any children a 36-month decrease ($p < 0.05$) in the preferred time to wait.

Similar to the education heterogeneity analysis, the pattern of results for starting contraceptives is consistent with the results for delaying childbearing. Specifically, in the Kenya sample where women without young children at home who experience a good growing season want to delay childbearing, they also are 50 percentage points more likely to start using family planning (Table 3, Panel C, Column 5, Row 6), relative to women with older children (with an overall effect of 48.7 percentage points, $p < 0.01$).

For the other outcomes and countries, such as the decision to discontinue family planning, recent childbearing does not moderate the effect of growing season quality. In other words, the effect of a good growing season is the same for women regardless of whether they had a child recently (within the past year), less recently (more than one year ago), or have no children at home.

7. Discussion

Women and children face unique risks associated with food insecurity, risks which are likely to increase with climate change and in communities that are dependent on rainfed agriculture. Scholarship examining the climate change-related risks women face and the strategies they use to manage these risks is limited (Lama et al., 2020; Lau et al., 2021). And, despite the theorized importance of agriculture and food security in connecting climate to individual fertility outcomes, few studies directly consider local growing season conditions in their assessments (e.g., Sellers and Gray 2019, Eissler, Thiede and Strube 2019, Alam and Pörtner 2018). In this analysis we investigate the ways that local growing season quality is associated with different dimensions of fertility and childbearing – namely fertility intentions and family planning use. We integrate ideas of fertility behavior being impacted in unique ways in a context of insecurity (Eissler et al., 2019; Trinitapoli and Yeatman, 2018; Trinitapoli and Yeatman, 2011) with those that consider the ways seasonal food production shapes resources and decision-making (Eissler et al., 2019; Hill et al., 2019; Sellers and Gray, 2019), and the seasonal pattern of fertility (Barreca et al., 2018;

Dorélien, 2016; Lam and Miron, 1991).

Our analysis advances the growing body of empirical work on environment and fertility preferences by directly considering the role of growing season conditions rather than relying on temperature or precipitation and inferring that they act through agricultural pathways. The results of our analysis suggest that growing season quality is indeed associated with childbearing goals and contraceptive use but highlights the importance of individual factors like education and birth spacing. We note that because NDVI is correlated to rainfall and temperature, other aspects of temperature and rainfall (e.g., waterborne illness, heat stress) not related to food production or month, may also be at play. Moreover, the results suggest that these relationships are not consistent across different countries, suggesting that women face unique constraints and opportunities in different settings. These complex findings highlight the importance of operationalizing environmental variables to reflect conceptual models of how climate change, weather, or agriculture affects individual-level fertility choices and behaviors (Grace et al., 2020).

Overall, we show that women in some settings do seem to shift their short-term behaviors and goals in response to growing season quality. Specifically, our results suggest that a good growing season in the interview year is associated with an increase in the probability of desiring a child in the future in the Kenya sample, a decrease in desired time before having another child in Uganda, and a greater likelihood of discontinuing family planning in Uganda. Dorélien (2016) demonstrated that births follow a seasonal pattern in sub-Saharan Africa, but with significant variation by geography, maternal education, and rural locale. Our findings build on past literature that suggests that point to an agricultural mechanism through which fertility preferences, timing, and behaviors are impacted by growing season quality, which in turn may contribute to a seasonal pattern of births (e.g., Panter-Brick 1996, Mosher 1979).

Our results on fertility preferences in the Kenya sample also provide supporting evidence for the hypothesis that households update beliefs about the future and ability to support a larger family based on growing season quality (Eissler et al., 2019; Sasson and Weinreb, 2017). Eissler et al. (2019) find that an increase in temperature and precipitation are associated with decreases in ideal family size and desire to have children, which they interpret as indicative of women seeking to reduce demands on household resources during times of adverse agricultural conditions. By examining the effect of growing season quality on fertility preferences and contraceptive behavior, our analysis supports that interpretation: in the Kenya sample a good growing season is associated with an increased desire for children, or conversely a bad growing season is associated with a lower desire for children.

Our results are also consistent with the scholarship that suggests that childbearing goals and spacing behaviors are a “moving target” and reflect individual- and household-level responses to changing conditions (Hayford and Agadjanian, 2017; Yeatman et al., 2013). The pattern of results for Uganda, in particular, demonstrate a cohesive picture of women strategically responding to changing agricultural conditions by updating both their preferences around childbearing timing (e.g., when they would next like to have a child) and taking action to achieve those goals (e.g., adjusting their use of family planning). The benefits of actively adjusting behavior in response to changing growing season conditions can be seen in child health outcomes – a recent analysis found that a good growing season the year before pregnancy can offset the negative impact of the hunger period on birthweight (Grace et al., 2020).

We also examined heterogeneity of the main results by education and time since most recent birth and observe many differential relationships that are masked by simply looking at average effects. First, consistent with other empirical findings, education seems to matter quite a bit in moderating the relationship between environmental factors and reproductive health outcomes (Eissler et al., 2019; Sellers and Gray, 2019). However, in contrast to other studies, we find that women both with and without formal education respond to environmental shocks by adjusting either fertility goals and aspirations or family planning use in different ways. For example, in Burkina Faso we found that women who had completed more than primary school were significantly more likely to want to delay childbearing and start using a method of family planning after experiencing a good growing season. While for fertility preferences and contraceptive use in Uganda and the Kenya sample, more and less educated women adjusted their behavior in similar ways in response to growing season quality, suggesting more sophisticated planning and strategy around childbearing than is often assumed of people who lack formal education.

We saw that time since the woman’s most recent birth was important with respect to the relationship between NDVI and fertility preferences. In particular, the combination of birth spacing/timing relative to a recent birth and local growing season conditions appears to tell a very consistent story among women in the Kenya sample: for women who gave birth very recently (within the year prior to their interview) and thus have a young child at home, a good growing season is associated with wanting to wait longer before having their next child, which they act on by increasing use of contraceptives. In the Kenya sample and Uganda, women without children were more likely to want to have children in the future in response to a good growing season, relative to those who currently have older children at home. These results suggest that women and households work to time pregnancies/births in an effort to optimize their child’s health through factors they have more control over (e.g., spacing) but with attention to locally relevant factors related to food security.

We also demonstrate that thinking conceptually about the timing of exposure matters by examining growing season conditions in two different time periods. We see that in general, growing season quality measured more closely to the interview appears to be the more relevant time period for impacting fertility preferences in these settings. However, in some cases, the prior year’s growing season also had an independent effect. For example, in Uganda we observe the opposite effect of growing season quality in the interview year compared to the previous year on both preferred time to wait before having another child and probability of discontinuing family planning, suggesting how the decisions or preferences of prior years may modify how growing season impacts in year *t*.

Additionally, our analysis demonstrates how using different measures to approximate growing season quality, specifically a subseasonal and full season measure, can be helpful for understanding local seasonal variation and issues related to food security (Davenport et al., 2021; Shukla et al., 2021). In these countries, we found the subseasonal measure was generally a more relevant factor determining childbearing aspirations and contraceptive use, although the full season measures were typically similar, suggesting that individuals react to conditions early on in the growing season. This finding has clear implications policies or interventions focused on reproductive health service delivery. For example, our results imply that in Uganda a good growing season was associated with wanting a pregnancy sooner and an increased desire to discontinue family planning; conversely a particularly bad growing season was associated with wanting to wait longer before having a child and greater likelihood of starting contraceptive use. Policies that prioritize reproductive autonomy would ensure women are able to remove or discontinue contraceptives when they want to become pregnant and access contraception when they wish to avoid or delay pregnancy (Nandagiri, 2021; Senderowicz, 2020). If the quality of the growing season can be detected early with subseasonal measures, then it becomes more feasible to ensure women have sufficient access to vital family planning services.

There are several important limitations to our analysis. First, we approximate the quality of the agricultural growing season using a remotely sensed vegetation measure (NDVI), rather than direct measurements of production or yield. Although imperfect, using NDVI allows us to approximate growing season conditions over a long time frame and in multiple countries at a very fine level of spatial resolution (Brown et al., 2014; Shukla et al., 2021; Vrieling et al., 2008). Additionally, due to limitations of the PMA data, we are not able to capture abortions (spontaneous or induced) or (partner) migration, both of which could impact fertility preferences, childbearing goals, and family planning use. The PMA data is also limited in information provided on coping strategies that individuals and families rely on when faced with environmental shocks, such as a poor growing season.

As agricultural production becomes increasingly variable due to climate change, it is important to develop a better understanding of the ways in which individuals respond. One particularly understudied aspect is women's fertility and reproductive health, including use of family planning services. Our analysis sheds light on the unique ways women are impacted by and respond to seasonal conditions. Changes in fertility and reproductive health outcomes more broadly should be better incorporated into policies and planning around climate change and agricultural impacts. Moreover, this work highlights the importance of reliable and diverse family planning service availability as women may want to stop or start according to seasonal, and even subseasonal, growing season quality.

CRediT authorship contribution statement

Nina Brooks: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Kathryn Grace:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition. **Devon Kristiansen:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **Shraddhanand Shukla:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Molly E. Brown:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data are publicly available but researchers must obtain it themselves.

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Appendix A. Supplementary data

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References

Alam, S.A., Pörtner, C.C., 2018. Income shocks, contraceptive use, and timing of fertility. J. Dev. Econ. 131, 96–103. https://doi.org/10.1016/j.jdeveco.2017.10.007.
Ameyaw, E.K., Budu, E., Sambah, F., Baatiema, L., Appiah, F., Seidu, A.-A., Ahinkorah, B. O., 2019. Prevalence and determinants of unintended pregnancy in sub-Saharan Africa: A multi-country analysis of demographic and health surveys. PLoS One 14, e0220970.
Ayanlade, A., Radeny, M., Morton, J.F., 2017. Comparing smallholder farmers' perception of climate change with meteorological data: A case study from southwestern Nigeria. Weather Clim. Extremes 15, 24–33. https://doi.org/10.1016/j.wace.2016.12.001.
Bakhtsiyarava, M., Grace, K., Nawrotzki, R.J., 2018. Climate, Birth Weight, and Agricultural Livelihoods in Kenya and Mali. Am. J. Public Health 108, S144–S150. https://doi.org/10.2105/AJPH.2017.304128.
Barreca, A., Deschenes, O., Guldi, M., 2018. Maybe Next Month? Temperature Shocks and Dynamic Adjustments in Birth Rates. Demography 55, 1269–1293. https://doi.org/10.1007/s13524-018-0690-7.
Barreca, A., Schaller, J., 2020. The impact of high ambient temperatures on delivery timing and gestational lengths. Nat. Clim. Chang. 10, 77–82. https://doi.org/10.1038/s41558-019-0632-4.
Bartholome, E., 1988. Radiometric measurements and crop yield forecasting Some observations over millet and sorghum experimental plots in Mali. Int. J. Remote Sens. 9 https://doi.org/10.1080/01431168808954959.
Battude, M., Al Bitar, A., Morin, D., Cros, J., Huc, M., Marais Sicre, C., Le Dantec, V., Demarez, V., 2016. Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. Remote Sens. Environ. 184, 668–681. https://doi.org/10.1016/j.rse.2016.07.030.
Becquey, E., Delpeuch, F., Konaté, A.M., Delsol, H., Lange, M., Zoungrana, M., Martin-Prevel, Y., 2012. Seasonality of the dietary dimension of household food security in urban Burkina Faso. Br. J. Nutr. 107, 1860–1870. https://doi.org/10.1017/S0007114511005071.
Blackmore, I., 2021. The impact of seasonality and climate variability on livelihood security in the Ecuadorian Andes. Climate. Risk Manage. 15.
Bledsoe, C., Banja, F., Hill, A.G., 1998. Reproductive Mishaps and Western Contraception: An African Challenge to Fertility Theory. Popul. Dev. Rev. 24, 15. https://doi.org/10.2307/2808121.
Bongaarts, J., 1980. Does malnutrition affect fecundity? A summary of evidence. Science 208, 564–569.
Bongaarts, J., 2011. Can family planning programs reduce high desired family size in Sub-Saharan Africa? Int. Perspect. Sex. Reprod. Health 37, 209–216. https://doi.org/10.1363/3720911.
Brauner-Otto, S.R., Axinn, W.G., Ghimire, D.J., 2007. The Spread of Health Services and Fertility Transition. Demography 44, 747–770. https://doi.org/10.1353/dem.2007.0041.
Brown, M.E., de Beurs, K.M., 2008. Evaluation of multi-sensor semi-arid crop season parameters based on NDVI and rainfall. Remote Sensing of Environment, Earth Observations for Terrestrial Biodiversity and Ecosystems Special Issue 112, 2261–2271. https://doi.org/10.1016/j.rse.2007.10.008.
Brown, M.E., Pinzon, J.E., Prince, S.D., 2008. Using Satellite Remote Sensing Data in a Spatially Explicit Price Model: Vegetation Dynamics and Millet Prices. Land Econ. 84, 340–357. https://doi.org/10.3368/le.84.2.340.
Brown, M.E., Grace, K., Shively, G., Johnson, K.B., Carroll, M., 2014. Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. Popul. Environ. 36, 48–72. https://doi.org/10.1007/s11111-013-0201-0.
Brown, M.E., Backer, D., Billing, T., White, P., Grace, K., Doocy, S., Huth, P., 2020. Empirical studies of factors associated with child malnutrition: highlighting the evidence about climate and conflict shocks. Food Sec. 12, 1241–1252. https://doi.org/10.1007/s12571-020-01041-y.
Choi, Y., Fabic, M.S., Adetunji, J., 2016. Measuring Access to Family Planning: Conceptual Frameworks and DHS Data: Measuring Access to Family Planning: Conceptual Frameworks and DHS Data. Stud. Fam. Plann. 47, 145–161. https://doi.org/10.1111/j.1728-4465.2016.00059.x.
Cooper, M., Brown, M.E., Azzarri, C., Meinzen-Dick, R., 2019a. Hunger, nutrition, and precipitation: evidence from Ghana and Bangladesh. Popul. Environ. 41, 151–208. https://doi.org/10.1007/s11111-019-00323-8.
Cooper, M.W., Brown, M.E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., Silva, J., Zvoleff, A., 2019b. Mapping the effects of drought on child stunting. PNAS 116, 17219–17224. https://doi.org/10.1073/pnas.1905228116.
Davenport, F., Dorélien, A., Grace, K., 2020. Investigating the linkages between pregnancy outcomes and climate in sub-Saharan Africa. Popul. Environ. 41, 397–421. https://doi.org/10.1007/s11111-020-00342-w.
Davenport, F.M., Shukla, S., Turner, W., Funk, C., Krell, N., Harrison, L., Husak, G., Lee, D., Peterson, S., 2021. Sending out an SOS: using start of rainy season indicators for market price forecasting to support famine early warning. Environ. Res. Lett. 16, 084050 https://doi.org/10.1088/1748-9326/ac15cc.
Dimitrova, A., 2021. Seasonal droughts and the risk of childhood undernutrition in Ethiopia. World Dev. 141, 105417 https://doi.org/10.1016/j.worlddev.2021.105417.
Dorélien, A., 2016. Birth seasonality in Sub-Saharan Africa. DemRes 34, 761–796. https://doi.org/10.4054/DemRes.2016.34.27.
Eissler, S., Thiede, B.C., Strube, J., 2019. Climatic variability and changing reproductive goals in Sub-Saharan Africa. Glob. Environ. Chang. 57, 101912 https://doi.org/10.1016/j.gloenvcha.2019.03.011.
Famine Early Warning Systems Network, 2021a. Burkina Faso. Available at: https://fews.net/west-africa/burkina-faso.
Famine Early Warning Systems Network, 2021b. Kenya. Available at: https://fews.net/east-africa/kenya.
Famine Early Warning Systems Network, 2021c. Uganda. Available at: https://fews.net/east-africa/uganda.
FAO's Food and Agriculture Policy Decision Analysis (FADPA), 2014. Country Fact Sheet on Food and Agriculture Trends. Burkina Faso, FAO.

FAO's Food and Agriculture Policy Decision Analysis (FADPA), 2015a. Country Fact Sheet on Food and Agriculture Trends. Uganda, FAO.

Findley, S.E., 1994. Does drought increase migration? A study of migration from rural Mali during the 1983–1985 drought. Int. Migr. Rev. 28, 539–553.

Grace, K., 2017. Considering climate in studies of fertility and reproductive health in poor countries. Nat. Clim. Chang. 7, 479–485. https://doi.org/10.1038/nclimate3318.

Grace, K., Nagle, N.N., 2015. Using High-Resolution Remotely Sensed Data to Examine the Relationship Between Agriculture and Fertility in Mali. Prof. Geogr. 67, 641–654. https://doi.org/10.1080/00330124.2015.1032899.

Grace, K., Lerner, A.M., Mikal, J., Sangli, G., 2017. A qualitative investigation of childbearing and seasonal hunger in peri-urban Ouagadougou, Burkina Faso. Popul. Environ. 38, 369–380. https://doi.org/10.1007/s11111-016-0268-5.

Grace, K., Billingsley, S., Van Riper, D., 2020. Building an interdisciplinary framework to advance conceptual and technical aspects of population-environment research focused on women's and children's health. Soc Sci Med 250, 112857. https://doi.org/10.1016/j.socscimed.2020.112857.

Hampshire, K., 2006. Flexibility in Domestic Organization and Seasonal Migration among the Fulani of Northern Burkina Faso. J. Int. African Institute 76, 402–426.

Handa, S., Mlay, G., 2006. Food consumption patterns, seasonality and market access in Mozambique. Dev. South. Afr. 23, 541–560. https://doi.org/10.1080/03768350600929249.

Hayford, S.R., Agadjanian, V., 2017. Determined to stop? Longitudinal analysis of the desire to have no more children in rural Mozambique. Popul. Stud. 71, 329–344. https://doi.org/10.1080/00324728.2017.1334957.

Hertrich, V., Lesclingand, M., 2012. Adolescent migration and the 1990s nuptiality transition in Mali. Popul. Stud. 66, 147–166. https://doi.org/10.1080/00324728.2012.669489.

Hill, R., Skoufias, E., Maher, B., 2019. The Chronology of a Disaster. World Bank, Washington, DC. https://doi.org/10.1596/31721.

Huete, A., Justice, C., Liu, H., 1994. Development of vegetation and soil indices for MODIS-EOS. Remote Sens. Environ. 49, 224–234. https://doi.org/10.1016/0034-4257(94)90018-3.

Husak, G.J., Funk, C.C., Michaelsen, J., Magadzire, T., Goldsberry, K.P., 2013. Developing seasonal rainfall scenarios for food security early warning. Theor. Appl. Climatol. 114, 291–302. https://doi.org/10.1007/s00704-013-0838-8.

Jiggins, J., 1986. Women and Seasonality: Coping with Crisis and Calamity. IDS Bull. 17, 9–18. https://doi.org/10.1111/j.1759-5436.1986.mp17003003.x.

Lam, D.A., Miron, J.A., 1991. Temperature and the Seasonality of Births. In: Zorgniotti, A.W. (Ed.), Temperature and Environmental Effects on the Testis. Springer, US, Boston, MA, pp. 73–88. https://doi.org/10.1007/978-1-4684-5913-5_7.

Lama, P., Hamza, M., Wester, M., 2020. Gendered dimensions of migration in relation to climate change. Clim. Dev. 1–11 https://doi.org/10.1080/17565529.2020.1772708.

Lau, J.D., Kleiber, D., Lawless, S., Cohen, P.J., 2021. Gender equality in climate policy and practice hindered by assumptions. Nat. Clim. Chang. 11, 186–192. https://doi.org/10.1038/s41558-021-00999-7.

Mosher, S.W., 1979. Birth Seasonality among Peasant Cultivators: The Interrelationship of Workload, Diet, and Fertility. Hum. Ecol. 7, 141–181.

Nandagiri, R., 2021. What's so troubling about 'voluntary' family planning anyway? A feminist perspective. Popul. Stud. 75, 221–234. https://doi.org/10.1080/00324728.2021.1996623.

Osgood, D., Powell, B., Diro, R., Farah, C., Enenkel, M., Brown, M., Husak, G., Blakeley, S., Hoffman, L., McCarty, J., 2018. Farmer Perception, Recollection, and Remote Sensing in Weather Index Insurance: An Ethiopia Case Study. Remote Sens. (Basel) 10, 1887. https://doi.org/10.3390/rs10121887.

Ovuka, M., Lindqvist, S., 2000. Rainfall variability in murang'a district, kenya: meteorological data and farmers' perception. Geogr. Ann. Ser. B 82, 107–119. https://doi.org/10.1111/j.0435-3676.2000.00116.x.

Panter-Brick, C., 1996. Proximate Determinants of Birth Seasonality and Conception Failure in Nepal. Popul. Stud. 50, 203–220. https://doi.org/10.1080/0032472031000149306.

Randell, H., Gray, C., 2019. Climate change and educational attainment in the global tropics. PNAS 116, 8840–8845. https://doi.org/10.1073/pnas.1817480116.

Randell, H., Jiang, C., Liang, X.-Z., Murtugudde, R., Sapkota, A., 2021. Food insecurity and compound environmental shocks in Nepal: Implications for a changing climate. World Dev. 145, 105511 https://doi.org/10.1016/j.worlddev.2021.105511.

Rao, N., Lawson, E.T., Raditloaneng, W.N., Solomon, D., Angula, M.N., 2019. Gendered vulnerabilities to climate change: insights from the semi-arid regions of Africa and Asia. Clim. Dev. 11, 14–26. https://doi.org/10.1080/17565529.2017.1372266.

Rasmussen, M.S., 1997. Operational yield forecast using AVHRR NDVI data: Reduction of environmental and inter-annual variability. Int. J. Remote Sens. 18, 1059–1077. https://doi.org/10.1080/014311697218575.

Rasmussen, M.S., 1998. Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part I. Assessment of net primary production. Int. J. Remote Sens. 19, 97–117. https://doi.org/10.1080/014311698216459.

Ross, J., Stover, J., 2013. Use of modern contraception increases when more methods become available: analysis of evidence from 1982–2009. Glob Health Sci. Pract. 1, 203–212. https://doi.org/10.9745/GHSP-D-13-00010.

Sasson, I., Weinreb, A., 2017. Land cover change and fertility in West-Central Africa: rural livelihoods and the vicious circle model. Popul. Environ. 38, 345–368. https://doi.org/10.1007/s11111-017-0279-x.

Sellers, S., Gray, C., 2019. Climate shocks constrain human fertility in Indonesia. World Dev. 117, 357–369. https://doi.org/10.1016/j.worlddev.2019.02.003.

Senderowicz, L., 2020. Contraceptive Autonomy: Conceptions and Measurement of a Novel Family Planning Indicator. Stud. Fam. Plann. 51, 161–176. https://doi.org/10.1111/sifp.12114.

Shukla, S., Husak, G., Turner, W., Davenport, F., Funk, C., Harrison, L., Krell, N., 2021. A slow rainy season onset is a reliable harbinger of drought in most food insecure regions in Sub-Saharan Africa. PLoS One 16, e0242883.

Smith-Greenaway, E., 2016. Premarital childbearing in sub-Saharan Africa: Can investing in women's education offset disadvantages for children? SSM - Population Health 2, 164–174. https://doi.org/10.1016/j.ssmph.2016.02.001.

Sobotka, T., Skirbekk, V., Philipov, D., 2011. Economic Recession and Fertility in the Developed World. Popul. Dev. Rev. 37, 267–306. https://doi.org/10.1111/j.1728-4457.2011.00411.x.

Solon, G., Haider, S.J., Wooldridge, J.M., 2015. What Are We Weighting For? J. Hum. Resour. 50, 301–316.

Stige, L.C., Stave, J., Chan, K.-S., Ciannelli, L., Pettorelli, N., Glantz, M., Herren, H.R., Stenseth, N.C., 2006. The effect of climate variation on agro-pastoral production in Africa. PNAS 103, 3049–3053. https://doi.org/10.1073/pnas.0600057103.

Thiede, B.C., Gray, C., 2020. Climate exposures and child undernutrition: Evidence from Indonesia. Soc Sci Med 265, 113298. https://doi.org/10.1016/j.socscimed.2020.113298.

Trinitapoli, J., Yeatman, S., 2011. Uncertainty and Fertility in a Generalized AIDS Epidemic. Am. Sociol. Rev. 76, 935–954. https://doi.org/10.1177/0003122411427672.

Trinitapoli, J., Yeatman, S., 2018. The Flexibility of Fertility Preferences in a Context of Uncertainty: Flexibility of Fertility Preferences in a Context of Uncertainty. Popul. Dev. Rev. 44, 87–116. https://doi.org/10.1111/padr.12114.

Vaitla, B., Devereux, S., Swan, S.H., 2009. Seasonal Hunger: A Neglected Problem with Proven Solutions. PLoS Med. 6, e1000101.

Van Bavel, J., 2010. Second birth rates across europe: interactions between women's level of education and child care enrolment. Populationyearbook 8, 107–138. https://doi.org/10.1553/populationyearbook2010s107.

Van Bavel, J., Klesment, M., 2017. Educational Pairings, Motherhood, and Women's Relative Earnings in Europe. Demography 54, 2331–2349. https://doi.org/10.1007/s13524-017-0621-z.

Vrieling, A., de Beurs, K.M., Brown, M.E., 2008. Recent trends in agricultural production of Africa based on AVHRR NDVI time series. Remote Sens. Agricult., Ecosyst. Hydrol. X. 231–240.

Yao, J., Murray, A.T., Agadjanian, V., Hayford, S.R., 2012. Geographic influences on sexual and reproductive health service utilization in rural Mozambique. Appl. Geogr. 32, 601–607. https://doi.org/10.1016/j.apgeog.2011.07.009.

Yeatman, S., Sennott, C., Culpepper, S., 2013. Young Women's Dynamic Family Size Preferences in the Context of Transitioning Fertility. Demography 50, 1715–1737. https://doi.org/10.1007/s13524-013-0214-4.