Climate Risk Management 47 (2025) 100683

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Impact of current and historical climate shocks on crop diversification in Zambia: Insights from household- and district-level observations

Junren Wang [a], Megan Konar [a,*], Patrese Nicole Anderson [b], Protensia Hadunka [c], Brian Mulenga [d]

[a] Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, United States of America
[b] Climate Hazards Center, University of California, Santa Barbara, United States of America
[c] Agricultural and Consumer Economics Department, University of Illinois at Urbana-Champaign, United States of America
[d] Indaba Agricultural Policy Research Institute, Lusaka, Zambia

A R T I C L E I N F O

Keywords:
Crop diversification
Smallholder agriculture
Weather extremes
Zambia

A B S T R A C T

Crop diversification is a farming practice for risk management prevalent in smallholder agriculture, offering adaptive benefits against challenges like climate change, price fluctuations, and crop disease. Despite its importance, there is a lack of comprehensive understanding of the relationship of crop diversification and current and historical climate shock. Our study seeks to bridge this gap through statistical analysis of household- and district-level data in Zambia. Specifically, we use the Pooled Fractional Probit (PFP) estimator to develop regression models for crop diversification, analyzing 6625 households for 3 years and 74 districts for 9 years, using Rural Agriculture Living Survey (RALS) and Crop Forecast Survey (CFS) datasets, respectively. Simpson's Diversity Index (SDI) of crops serves as the dependent variable and is consistently higher at the district level than at the household level, suggesting that aggregation at larger scales may mask localized monoculture vulnerabilities. Our findings reveal that both current and historical climate shocks significantly influence crop diversification decisions at both the household and district levels in Zambia. Heat stress and rainfall deficits during the planting season promote crop diversification, but their effects vary due to the diverse agroecological conditions and crop characteristics in different areas. Historical climate shocks prompt farmers to diversify as a long-term resilience strategy. This study emphasizes the complex, scale-dependent drivers of crop diversification in response to climate shocks, providing valuable insights for policy development in climate-resilient agricultural strategies.

1. Introduction

Agriculture in developing countries faces increasing risks due to climate variability, with extreme weather events like droughts and floods posing serious challenges to crop yields and food security (Wheeler and Von Braun, 2013; Zougmoré et al., 2018). In response, crop diversification has emerged as one of the key adaptation strategies for managing climate shocks, particularly in smallholder agriculture systems. By spreading risk across different crop types, farmers can better manage the adverse impacts of climate shocks, thereby enhancing resilience and reducing vulnerability to climate extremes (Seo, 2010; Auffhammer and Carleton,

* Corresponding author.
E-mail address: mkonar@illinois.edu (M. Konar).

https://doi.org/10.1016/j.crm.2024.100683
Received 6 March 2024; Received in revised form 11 November 2024; Accepted 11 December 2024

Available online 21 December 2024

2018; Birthal and Hazrana, 2019). Crop diversification has been promoted as important climate-smart agriculture and conservation agriculture strategy to mitigate the adverse effects of climate variability (Arslan et al., 2018; Thierfelder and Mhlanga, 2022; Hassan and Knight, 2023). There is thus a need to investigate the determinants of crop diversification decisions amidst various climate risks to better inform agricultural development interventions.

This study aims to explore the determinants of crop diversification decisions at the household and subnational (district) levels within the climate shock context, using Zambia as an example. Zambia's agriculture production is dominated by smallholder farmers who are almost entirely reliant on rainfall for their production, which makes the sector vulnerable to climatic shocks (Makondo et al., 2014; Siatwiinda et al., 2021). Climate projections models suggest an increase in the frequency and intensity of droughts and floods in the future, which will significantly impact smallholder farmers (Libanda and Ngonga, 2018). Crop diversification has emerged as a central policy priority for the Zambian government within the agricultural sector, serving as a climate adaptation and measure and enhancing resilience (Chikobola and Tembo, 2018). The rain-fed, smallholder-driven agriculture pattern and high exposure to climate shocks present a common dilemma for most countries in Africa (Niles and Salerno, 2018; Lamptey, 2022). Understanding crop diversification in Zambia could offer broader insights into the enablers and barriers faced by Sub-Saharan African agriculture in the face of global environmental changes. Therefore, a detailed examination of crop diversification determinants in Zambia is not only important for enhancing the country's agricultural resilience and economic stability but also has implications for other regions confronting similar agricultural challenges.

Extreme climate events, such as droughts, floods, and temperature fluctuations, play a significant role in shaping agricultural decisions, particularly crop diversification (Acevedo et al., 2020). Several studies have examined how climate factors impact crop diversification decisions. Miao et al. (2016) found a negative effect of monthly precipitation before the planting season on maize acreage at the county level in the US. Salazar-Espinoza et al. (2015) observed that farmers altered their land use following droughts and floods. There is also evidence that farmers adapt to shifting patterns of precipitation by changing crop varieties and types (Seo and Mendelsohn, 2008; Kurukulasuriya and Mendelsohn, 2008), or converting agricultural land to alternative uses (Feres et al., 2008). Kumar et al. (2018) observed that increased rainfall and minimum temperatures negatively impacted crop diversification in India. Exposure to historical extreme weather events and long-term climate variability can encourage crop diversification to enhance resilience; for example, this has been observed in studies conducted in Kenya (Bozzola and Smale, 2020), Malawi and Tanzania (Makate et al., 2023). Additionally, climate change affects farmers' perception of climate shocks, influencing their response to short-term climate abnormality and disaster (Seo and Mendelsohn, 2008). Some studies have extended the discussion to include variables affected by climate change, for example, the water availability, natural ecosystems and forests (Labeyrie et al., 2021). This study seeks to fill this gap by examining how both immediate and historical climate factors influence crop diversification decisions, thereby providing a more nuanced understanding of how extreme climate impacts shape agricultural resilience strategies.

Our work stands apart from existing research on the determinants of crop diversification in the following respect: Firstly, we incorporate a more comprehensive set of climate and weather variables, including month indicators in the current year, previous weather shocks, and long-term climate variations based on temperature and precipitation conditions. This approach contrasts with most existing studies, which typically focus on only one of these factors (Rahman and Kazal, 2015; Arslan et al., 2018; Goldberg et al., 2021), thereby neglecting the multifaceted impacts of climatic conditions. Secondly, our analysis extends beyond the household level, which is the primary focus of most existing research (Arslan et al., 2018; Goldberg et al., 2021; Li et al., 2021), to include determinants at both the household and district levels. Large spatial scale diversification is relatively unexplored, with limited studies examining the influence of county and district-level factors on crop diversification (Kumar et al., 2018). Thirdly, our study offers a more nuanced understanding of spatial heterogeneity and temporal granularity in crop diversification. We compare analytical results across four distinct agro-ecological zones to better capture spatial differences. Meanwhile, we use monthly climate indices during the planting season, rather than annual averages as most previous studies (Rahman, 2016; Kumar et al., 2018), to provide a more detailed view of the monthly climatic impacts on crop diversification. Lastly, we adopt a more robust estimator—Pooled Fractional Probit (PFP) proposed by Papke and Wooldridge (2008) to address the bounded nature of the crop diversification index. This approach allows for the non-linear relationship between the diversification index and other factors, thereby improving the reliability and validity of our findings (Schlenker and Roberts, 2006, 2009).

This study aims to explore the determinants of crop diversification in Zambia at both the household and district levels, focusing on the roles of current climate shocks (such as heat stress and rainfall deficits in planting season) and historical climate shock (heat stress and rainfall deficits over the last three years). By analyzing data at these different scales, we provide a holistic view of how climate influences crop diversification decisions, offering new insights into agricultural resilience strategies under changing climate conditions. Understanding these dynamics is particularly relevant for regions like Sub-Saharan Africa, where the impacts of climate change on agriculture are expected to be profound. The rest of the paper is organized as follows: Section 2 presents the data sources and methodologies utilized in this study. Section 3 details the findings, including both a descriptive analysis of crop diversification trends in Zambia and an in-depth examination of the factors influencing crop diversification, particularly focusing on weather and climate. The paper concludes with Section 5.

2. Data and methodologies

2.1. Study site

The case study country, Zambia, is a developing land-locked country in sub-Saharan Africa (SSA). The agricultural sector in Zambia accounted for 53% of the workforce and approximately 6% of the GDP of the whole country in 2016 (DataBank, 2023).

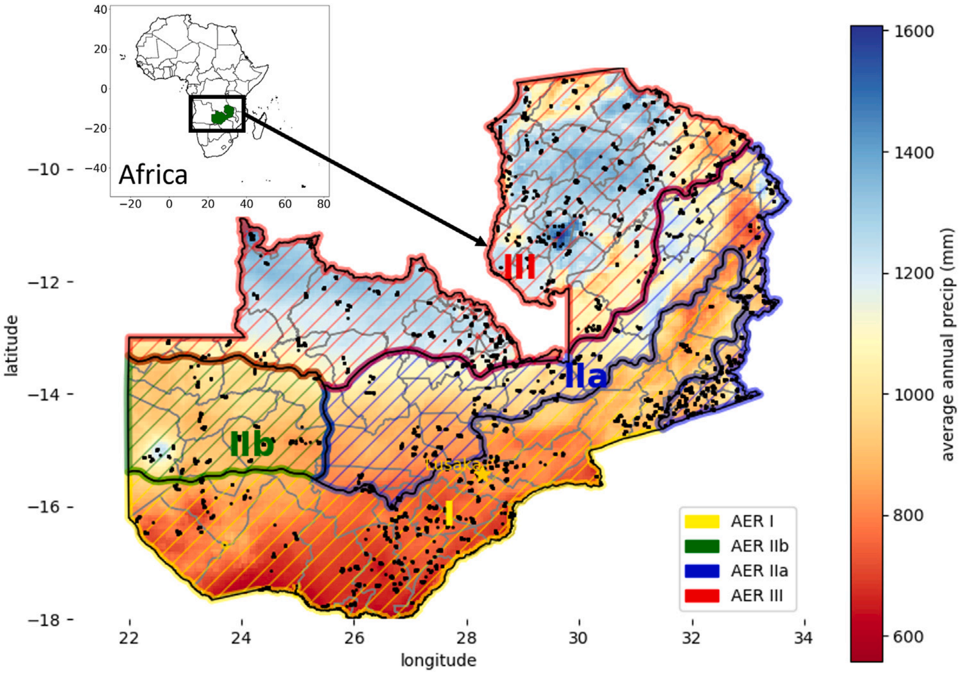

Fig. 1. Zambia's location and the agro-ecological regions. Zambia is located in south-central Africa, highlighted as a green polygon in the subplot. The main plot displays a choropleth map of average annual precipitation data from 1980 to 2020, along with the distribution of 6625 surveyed households (black points) and 74 district divisions (gray boundaries) in four agro-ecological regions (colored slashed region) of Zambia.

Agriculture is dominated by smallholders cultivating less than 20 hectares of land annually and mostly depending on rain-fed subsistence agriculture. Maize is the most widely grown crop in Zambia, serving as the main staple and providing about 46% calories for Zambian people as per the FAO 2020 food balance sheet (FAO, 2023).

Zambia has four distinct Agro-Ecological Regions (AER)—AERI, AERIIa, AERIIb, and AERIII, each with different climate conditions, as shown in Fig. 1. Rainfall in Zambia increases from the south (AER I) to the north (AER III). This varying precipitation pattern results in southern Zambia being primarily a maize belt, while northern Zambia is characterized as a cassava-maize belt. There are three agricultural seasons in Zambia: the hot and dry season (from mid-August to mid-November), the wet rainy season (from mid-November to April), and the cool dry season (from May to mid-August). Maize is mainly planted and grown during the rainy season and harvested in May and June.

Drought is a growing threat to food security in Zambia, as it is worsened by climate change (Libanda and Ngonga, 2018). Climate change is spatially heterogeneous in Zambia. Extreme weather is more and more noticeable in the Southern and Western provinces, where the national staple crop, maize, is widely planted (Kaluba et al., 2017). Maize's sensitivity to rainfall deficits during the growing season leads to concerns among farmers and consumers about the potential impact of climate shocks on food security. To promote crop diversification, the Zambian government has been piloting the electronic and flexible input subsidy under the Farmer Input Support Programme (FISP). This electronic voucher system (e-voucher) enables farmers to independently choose the inputs they wish to purchase with their allocated funds in the subsidy vouchers (Chikobola and Tembo, 2018; Chibbompa, 2018).

2.2. Data

2.2.1. Land area data

The household-level data on land area and livelihood context are extracted from the Rural Agricultural Livelihood Survey (RALS), implemented by Indaba Agricultural Policy Research Institute (IAPRI), Michigan State University's Department of Agricultural and Resource Economics, Central Statistical Office (CSO) and Ministry of Agriculture and Livestock (MAL). The district-level data on land area from 2010 to 2019 are obtained from the annual Crop Forecast Surveys (CFS) implemented by CSO and MAL. Both datasets are nationally representative. These two datasets each have their own advantages and disadvantages. The RALS is a three-wave panel survey, which captures data at the household scale, the smallest unit of crop diversification decision-making. The RALS was implemented in 2012, 2015, and 2019 to provide a comprehensive picture of Zambia's small and medium-scale farmers. In contrast, the district-level data provide spatially aggregate information but cover a longer temporal period.

The agricultural season in Zambia aligns with the rainy season, starting around November, when planting activities commence, and lasting until the following May, when harvesting activities begin. In the RALS dataset, farmers report their planting area for each crop for the 2010/2011, 2013/2014, and 2017/2018 agricultural seasons, along with household demographic characteristics.

We use district-level land area data for the agricultural seasons from 2009/2010 to 2018/2019 from the CFS. In this study, we refer to the harvest year instead of the survey or planting year.

2.2.2. Weather data

Weather variables are derived from two sources: (1) Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a monthly precipitation dataset with 0.05-degree resolution from the year 1981 to 2023 (Funk et al., 2015); and (2) Fifth generation of ECMWF atmospheric reanalyses of the global climate (ERA5), a daily air temperature dataset with 0.25 degree resolution from 1979 to 2020 (Hersbach, 2016). To calculate the weather variables for different households and districts, we collect the GPS coordinates of the households recorded in the RALS and the spatial coverage of districts from Global Map Zambia version 1.0 (International Steering Committee for Global Mapping and Zambia Survey Department, 2012). Weather variables for each household are the mean value within a 10 km radius circle centered on the household's location. The spatial mean values for the districts represent their respective overall conditions.

2.3. Empirical model

2.3.1. Variable definition

Crop diversification is commonly measured by the Simpson's Diversity Index (SDI), which considers both the number of crops and the allocation of cropland (Benin et al., 2004; Kumar et al., 2018; Mofya-Mukuka and Hichaambwa, 2018; Arslan et al., 2018). We follow the same definition as shown in Eq. (1):

$$SDI_n = 1 - \sum_{i=1}^{k} P_{ni}^2 \tag{1}$$

where, we consider a random sample of households or districts n = 1, …, N. SID_n is the Simpson's Diversity Index for sample n. P_{ni} is the area share of specific crop i for household or district n. Eleven crops are included in this study: maize, cassava,[1] sorghum, rice, millet, sunflower, groundnut, soyabean, seedcotton, common beans, and potato.

The empirical model is centered on estimating the effect of weather and climate variables on the crop diversification decision. We focus on the impact of extreme temperature and precipitation, which is mostly studied for maize, rice, and cereals (Davis et al., 2021). We include weather and climate-related variables at three different levels: (1) we include the monthly heat stress and rainfall deficit for beginning of the rain season (Oct, Nov, Dec). This variable indicates to the farmer how the weather during growing season is likely to be and might determine their crop diversification decision. Heat stress is defined as the number of days in a month when the maximum air temperature at 2 meters is at least 3 degrees Celsius higher than the long-term average monthly maximum air temperature from 1980 to 2020. The rainfall deficit is defined as the number of standard deviations by which the current precipitation is lower than the long-term average precipitation from 1980 to 2020. The definition of heat stress and rainfall deficit follows from Birthal and Hazrana (2019), who emphasized spatial heterogeneity. However, instead of using the annual average, we extend it to have a higher temporal resolution. (2) Leveraging the same definition of heat stress and rainfall deficit, we consider the maximum of the last three years' agricultural season's heat stress and rainfall deficit since farmers' decisions regarding crop selection and allocation in the current year are shaped not only by expected weather conditions but also by historical weather shocks () (3) Thirdly, we use the 10-year backward precipitation coefficient of variance to estimate the long-term climate change impact on the crop diversification change.

The role of weather and climate variables is studied in conjunction with a large number of covariates, including household demographics, market information, infrastructure, and government procurement. The reasons for controlling for these covariates are detailed in the Supporting Information.

2.3.2. Fractional probit model

As defined in Eq. (1), the Simpson's Diversity Index (SDI) is bounded between zero and one. The bounded property of the dependent variable makes standard linear models less preferable as the linear model may not accurately depict the impact of explanatory variables on SDI across the entire range of these variables. We follow the Pooled Fractional Probit (PFP) estimator for panel data developed by Papke and Wooldridge (2008), which is obtained by maximizing the pooled probit log-likelihood. The advantages of this nonlinear estimator include (1) there is no need to assume serial dependence in the response variable, (2) it addresses fractional responses, and (3) it is suitable for panel data that have a large cross-sectional dimension but a relatively small time dimension.

We consider a random sample of households or districts n = 1, …, N, for time period t= 1,.., T. For the household level, RALS is a short panel data set with 6625 households (after attrition) for 3 noncontinuous years, i.e., N = 19875. We follow the methodologies recommended in Wooldridge (2010), which have been used in Mofya-Mukuka and Hichaambwa (2018), Fung et al. (2020), to detect potential attrition bias in the RALS data. We fail to reject the null hypothesis of no attrition bias for all households and households within each agro-ecological region (detailed in the Supporting Information), indicating that attrition bias will not be a severe problem for this study. For the district level, CFS involves data on 74 districts for 9 years, i.e., N = 666. The spatial

[1] For perennial crop cassava, SDI value is calculated using the existing cassava land share for each study year at both the district and household levels, disregarding the planting year.

Table 1
Descriptive statistics of district-level regression variables.

Variable	2010–2012		2013–2015		2017–2019	
	mean	sd	mean	sd	mean	sd
SDI	0.52	0.15	0.54	0.15	0.55	0.14
heatstress_10	4.62	4.12	4.32	2.12	6.03	5.38
heatstress_11	3.28	2.62	7.80	4.97	6.01	4.20
heatstress_12	1.15	1.70	3.63	3.94	3.03	3.15
rainfall_deficit_10	0.54	0.44	0.33	0.33	0.49	0.45
rainfall_deficit_11	0.08	0.22	0.48	0.49	0.42	0.53
rainfall_deficit_12	0.21	0.27	0.21	0.44	0.36	0.47
heatstress_max3	18.84	8.01	26.99	13.00	47.00	24.54
rainfall_deficit_max3	1.94	0.49	1.90	0.54	2.37	0.68
rainfall_variation_lag1	2.08	0.77	2.06	0.75	1.90	0.73
last year fra maize procurement amount (10^4 MT)	1.22	1.88	1.09	1.18	0.43	0.62
Road_Density (km/km^2)	0.11	0.53	0.28	1.02	0.67	1.67

distribution of the households and districts is shown in Fig. 1. The conditional expectation of dependent variable SDI_{nt} is assumed to follow the standard normal cumulative distribution function (CDF) as specified in Eq. (2).

$$E(SDI_{nt}|X_{nt}, c_n) = \Phi(X_{nt}\beta + c_n),\ t = 1, \ldots, T \tag{2}$$

X_{nt} is a 1×K vector of explanatory variables for household/district n at time t. The explanatory variables are defined in Section 2.3.1. c_n is the individual unobserved characteristics. β refers to the parameters that need to be estimated.

In order to identify β, we follow the assumption of Papke and Wooldridge (2008) that c_n follows a normal distribution with mean $\psi + \bar{x}_n\xi$ and variance σ_a^2. Here, $\bar{x}_n$ represents the vector of time averages i.e., $T^{-1}\sum_1^T x_{nt}$.

According to the above assumptions, the new representation of the expectation of conditional SDI_{nt} is rewritten as Eq. (3), using the mixing property of normal distribution. The estimation of σ_a^2 can be achieved through maximum likelihood techniques.

$$E(SDI_{nt}|x_n) = \Phi[(\psi + x_{nt}\beta + \bar{x}_n\xi)/(1 + \sigma_a^2)^{\frac{1}{2}}] \tag{3}$$

The partial effect of explanatory variable x_{tj}, which is dropping the observation index n, depends on the value of other covariates and the unobserved heterogeneity. To understand the importance of the observed covariates, we average the partial effects across the distribution of c_n, to obtain the average partial effects (APE). According to Eq. (3) and the law of large numbers, a consistent estimate of APE could be represented by Eq. (4).

$$\frac{\partial N^{-1}\sum_{n=1}^{N}\Phi[(\psi + x_t\beta + \bar{x}_n\xi)/(1 + \sigma_a^2)^{\frac{1}{2}}]}{\partial x_{tj}} \tag{4}$$

The average partial effects are compared with the coefficients of a simple linear two-way fixed effect (FE) model. The two-way fixed effect model is a conventional way to effectively account for time-invariant unobserved heterogeneity at the individual level, thereby controlling for potential biases and improving the accuracy.

3. Results

3.1. Descriptive statistics of key variables

Tables 1 and 2 provide descriptive statistics for the dependent and independent variables at the household and district levels, respectively. The SDI at the district level shows a gradual increase over time, from 0.52 in 2010–2012 to 0.54 in 2013–2015, and 0.55 in 2017–2019. This upward trend suggests that crop diversification at the district level has generally increased over these periods. The mean SDI for districts above 0.5 indicates the inclusion of approximately three different crops, with one or two crops likely dominating the landscape. In contrast, the mean SDI value for household-level observations is below 0.5, meaning that on average, two or fewer types of crops are dominant. Both households and districts tables indicate gradual improvement in development indicators and infrastructure over time. Household-level data show improvements in asset values and off-farm income, whereas district-level data highlight increases in road density. Heat stress and rainfall deficits display variability across the years. For example, heat stress for October, November, and December declined from year 2011 to year 2014 but then increased again in year 2018, particularly for November. However, the intensity of historical shocks increased over time, as indicated by the rise in heatstress_max3 and rainfall_deficit_max3.

3.2. Determinants of crop diversification at the district level

Table 3 is district-level estimates from the linear Fixed Effect (FE) model and pooled fractional probit (PFP) model. The results obtained from different estimators for the diversification index exhibit slight differences in coefficient estimation and the level of statistical significance.

Table 2
Descriptive statistics of household-level regression variables.

Variable	ag_{year}2011		ag_{year}2014		ag_{year}2018	
	mean	sd	mean	sd	mean	sd
SDI	0.41	0.25	0.40	0.24	0.43	0.24
heatstress_10	8.21	3.76	4.37	2.44	6.33	3.52
heatstress_11	5.86	2.36	7.82	5.05	1.72	1.32
heatstress_12	0.36	0.89	5.47	4.01	0.71	1.23
rainfall_deficit_10	0.89	0.36	0.28	0.34	0.04	0.11
rainfall_deficit_11	0.32	0.34	0.37	0.34	0.07	0.19
rainfall_deficit_12	0.05	0.12	0.01	0.06	0.09	0.18
heatstress_max3	12.64	4.85	32.52	11.20	55.41	18.09
rainfall_deficit_max3	2.07	0.48	2.17	0.50	2.43	0.46
rainfall_variation_lag1	1.87	1.01	1.89	1.01	1.84	1.02
distance to the closest market (km)	26.26	31.09	24.11	28.91	22.24	26.52
irrigation asset[a] value (10^4ZMK)	0.03	0.97	0.06	1.86	1.11[b]	65.30
transportation asset[c] value (10^4ZMK)	0.06	0.15	0.09	0.25	0.12	0.31
information asset[d] value (10^4ZMK)	0.11	0.62	0.15	0.72	0.22	0.92
last year fra maize procurement amount[e] ((10^4 MT)	1.68	1.59	0.75	0.64	1.02	1.03
1=female household head	0.19	0.39	0.21	0.41	0.24	0.43
household head age	46.27	14.61	49.07	14.52	52.30	14.20
household dependent rate[f]	1.16	0.88	1.37	1.06	1.63	1.31
# of household member	6.08	2.69	6.38	2.76	6.50	2.88
total landholding (hectare)	2.39	2.28	2.26	2.36	2.33	2.50
off farm income (10^4 ZMK)	0.21	1.90	0.30	1.32	0.38	1.63
loan (10^4 ZMK)	0.02	0.39	0.02	0.14	0.03	0.24

[a] e.g., water pump.
[b] There are several extremely large entries that significantly increase the mean value and standard deviation. The large values are likely related to installations like water wells.
[c] e.g., bicycle or motorcycles.
[d] e.g., radios and cellphones.
[e] The district-level maize procurement amounts for each year are sourced from the Food Reserve Agency (FRA), a national agency mandated with management and administration of the country's strategic food reserves.
[f] The dependent rate of the household is defined as the ratio between the number of children (age <= 14) and old people (age >= 65) to the number of working adults (14 < age < 65).

For current planting season climate shocks, heatstress_10, heatstress_12, and rainfall_deficit_11 show a statistically significant positive association with crop diversification. This suggests that higher heat stress and rainfall deficits, particularly in October and December, encourage diversification, likely as an adaptive response to extreme weather conditions.

For historical climate shocks, heatstress_max3 (cumulative heat stress over the past three years) is positive and significant, indicating that recent high heat stress promotes crop diversification as a long-term adaptation strategy.

Road Density (Road_Density_km_km^2) has positive and significant coefficients in both PFP and FE models, suggesting that greater road density is linked to higher crop diversification. This may imply that improved market and transportation access fosters diversification by facilitating access to inputs and new markets.

3.3. Determinants of crop diversification at the household level

Table 4 is household-level estimates of the linear Fixed Effect (FE) model and pooled fractional probit (PFP) model.

For the current planting season, the positive and significant coefficient of heatstress_11 for household-level regression in both PFP and FE models suggests that increased heat stress in November is linked to higher crop diversification. This indicates that households may diversify in response to early-season stress. In contrast, heatstress_12 in December shows a negative and statistically significant coefficient for all observations, with a 10% significance level. Meanwhile, the positive and significant coefficient of rainfall_deficit_12 suggests that a December rainfall deficit promotes crop diversification, likely as an adaptation to water scarcity during critical growth periods.

For historical climate shocks, both heatstress_max3 (maximum heat stress over the last three years) and rainfall_deficit_max3 are positive and significant in both models, indicating that a history of high heat stress supports crop diversification as a risk management strategy.

Household demographics are considered only in the household-level regression, because it is challenging to find comparable demographic variables at the district level. Households with female heads tend to have less diversification, as do households with a high dependency rate. Conversely, households with a greater number of members and larger landholdings exhibit more diversification. These relationships are statistically significant and intuitive, as it is generally believed that households with more labor and social resources have a better opportunity to diversify. The results are consistent with previous studies focusing on the

Table 3
Results of district-level regression.

Variable	PFP			FE
	(1)	(2)	(3)	(4)
heatstress_10	0.0016	0.0022*	0.0026**	0.0029**
	(0.0014)	(0.0013)	(0.0013)	(0.0011)
heatstress_11	−0.0014	−0.0017	−0.0019	−0.0017*
	(0.0014)	(0.0014)	(0.0013)	(0.0011)
heatstress_12	0.0032*	0.0028*	0.0027*	0.0009
	(0.0018)	(0.0016)	(0.0016)	(0.0012)
rainfall_deficit_10	−0.0180	−0.0097	−0.0059	0.0152
	(0.0145)	(0.0146)	(0.0138)	(0.0123)
rainfall_deficit_11	0.0027	0.0068	0.0072	−0.0016
	(0.0139)	(0.0127)	(0.0120)	(0.0084)
rainfall_deficit_12	0.0205**	0.0181*	0.0166*	0.0168**
	(0.0097)	(0.0099)	(0.0097)	(0.0086)
heatstress_max3	_	0.0007**	0.0008***	0.0008***
		(0.0003)	(0.0003)	(0.0003)
rainfall_deficit_max3	_	0.0006	0.0003	−0.0012
		(0.0060)	(0.0058)	(0.0058)
rainfall_variation_lag1	_	_	−0.0219	−0.0169
			(0.0158)	(0.0138)
Road_Density_km_km^2	0.0251*	0.0245**	0.0237*	0.0210***
	(0.0135)	(0.0122)	(0.0122)	(0.0057)
fra_purchase_lag1	−0.0007	0.0023	0.0027	0.0028
	(0.0022)	(0.0027)	(0.0029)	(0.0029)
Observation (n)	666	666	666	666

* p<0.1.
** p<0.05.
*** p<0.01.

Standard errors are obtained by bootstrapping the 74 districts using 500 bootstrap replications for all the fractional probit models.

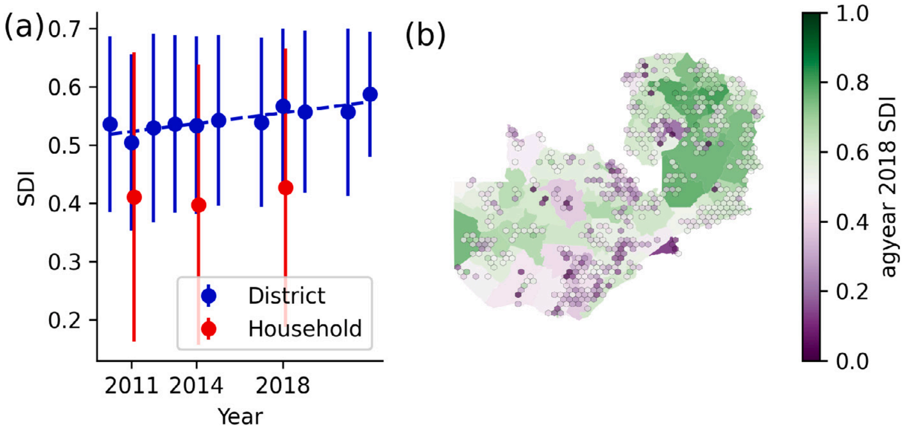

Fig. 2. (a) Time series of mean and standard deviation values for Simpson's Diversity Index (SDI) at the household (red) and district (blue) levels. (b) Spatial distribution of SDI for households (aggregated into a hexbin[2] plot) and districts in Zambia.

impact of household demographics (Benin et al., 2004; Shezongo-Macmillan, 2005; Mofya-Mukuka and Hichaambwa, 2018; Inoni et al., 2021).

We also run the regression for households in each agro-ecological region (AER) separately, and the results are presented in Table 5. Only the weather-related variables are included in the table, but we also controlled for all other covariates.

In Agro-Ecological Region (AER) I, the heatstress_10 and rainfall_deficit_11 and the rainfall_deficit_max3 show a positive and statistically significant relationship with crop diversification. High heat stress in November (heatstress_11), the conventional month for maize planting, is statistically significant and positively related to the SDI in AER IIa. Additionally, heatstress_max3 is also

[2] Hexbin plots with a grid size of 50 are used to address the overlapping household points problem. For each hexagon, values are aggregated using the 'mean' function.

Table 4
Results of household-level regression.

Variable	PFP			FE
	(1)	(2)	(3)	(4)
heatstress_10	−0.0000	−0.0003	−0.0003	−0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
heatstress_11	0.0016**	0.0020***	0.0020***	0.0020***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)
heatstress_12	−0.0019**	−0.0016*	−0.0016*	−0.0017*
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
rainfall_deficit_10	0.0073	−0.0018	−0.0018	−0.0030
	(0.0063)	(0.0066)	(0.0066)	(0.0065)
rainfall_deficit_11	−0.0022	0.0020	0.0020	0.0029
	(0.0068)	(0.0069)	(0.0069)	(0.0071)
rainfall_deficit_12	0.0392***	0.0236*	0.0237*	0.0219*
	(0.0120)	(0.0127)	(0.0127)	(0.0127)
heatstress_max3	_	0.0004***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)
rainfall_deficit_max3	_	0.0110***	0.0110***	0.0112***
		(0.0030)	(0.0031)	(0.0032)
rainfall_variation_lag1	_	_	0.0002	−0.0000
			(0.0029)	(0.0029)
dmarket	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
asset_irrigation	−0.0002	−0.0002	−0.0002	−0.0001**
	(0.0020)	(0.0021)	(0.0020)	(0.00003)
asset_transportation	0.0114	0.0112	0.0111	0.0096
	(0.0075)	(0.0074)	(0.0074)	(0.0074)
asset_information	−0.0025	−0.0025	−0.0024	−0.0015
	(0.0050)	(0.0051)	(0.0050)	(0.0020)
fra_purchase_lastyear	−0.0034	−0.0022	−0.0022	−0.0019
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
sexh	−0.0251**	−0.0246**	−0.0245**	−0.0253***
	(0.0099)	(0.0100)	(0.0100)	(0.0096)
ageh	0.0001	0.0001	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
dep_rat	−0.0039**	−0.0040**	−0.0040**	−0.0041**
	(0.0018)	(0.0018)	(0.0018)	(0.0017)
hhsize	0.0067***	0.0065***	0.0065***	0.0065***
	(0.0011)	(0.0011)	(0.0011)	(0.0010)
total_area	0.0132***	0.01337***	0.01338***	0.0135***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
other_income	0.0029	0.0030	0.0029	0.0000
	(0.0041)	(0.0041)	(0.0041)	(0.0012)
amt_loan	−0.0207	−0.0208	−0.0202	−0.0046
	(0.0142)	(0.0143)	(0.0139)	(0.0029)
Observation(N)	19 875	19 875	19 875	19 875

* p<0.1.
** p<0.05.
*** p<0.01.

Standard errors are obtained by bootstrapping the 6625 households using 500 bootstrap replications for all the fractional probit models.

statistically and positively related to the SDI. AER IIb and For AER III, the crop diversification is negatively and statistically significant related to the heatstress_10 and rainfall_variarion_lag1.

4. Discussions

4.1. Household and district level observations and crop diversification

This section examines crop diversification patterns across household and district levels in Zambia, exploring how spatial and temporal scales impact observed diversification trends.

Fig. 2(a) depicts a discernible upward trend in the Simpson's Diversity Index (SDI) over time, suggesting an increase in crop diversification over the study time period. Notably, the SDI values at the household level are consistently lower than those at the district level, despite the application of the same definition as given by Eq. (1). This discrepancy can be attributed to the fact that different specializations of households also contribute to diversification at the aggregate district level. The importance of scale in crop diversification assessments is twofold: On one hand, aggregation at a larger scale (district level) might obscure vulnerabilities

Table 5
Results of household-level regression for different agro-ecological region.

Variable	I	IIa	IIb	III
heatstress_10	0.0051**	−0.0004	0.0233***	−0.0033***
	(0.0022)	(0.0021)	(0.0070)	(0.0012)
heatstress_11	0.0021	0.0043***	0.0061	0.0009
	(0.0022)	(0.0015)	(0.0093)	(0.0010)
heatstress_12	0.0020	−0.0007	0.0374	−0.0044
	(0.0021)	(0.0016)	(0.0360)	(0.0034)
rainfall_deficit_10	0.0329*	−0.0045	0.1037	−0.0077
	(0.0186)	(0.0106)	(0.0753)	(0.0129)
rainfall_deficit_11	0.0238**	−0.0015	−0.1639*	−0.0092
	(0.0121)	(0.0163)	(0.0864)	(0.0129)
rainfall_deficit_12	−0.0438	0.0192	−0.1049	−0.0079
	(0.0307)	(0.0257)	(0.2555)	(0.0282)
heatstress_max3	−0.0000	0.0007***	0.0025	−0.0002
	(0.0003)	(0.0002)	(0.0022)	(0.0004)
rainfall_deficit_max3	0.0256***	0.0054	0.0252	0.0084*
	(0.0009)	(0.0085)	(0.0355)	(0.0044)
rainfall_variation_lag1	−0.0030	0.0010	0.0329	−0.0170**
	(0.0055)	(0.0040)	(0.0457)	(0.0084)
N	5739	5745	1227	7164

* p<0.1.
** p<0.05.
*** p<0.01.

stemming from localized (household) monoculture. Crop diversification plays a crucial role in enhancing food security and reducing poverty (Nahar et al., 2024; Fujimoto and Suzuki, 2025). Therefore, relying solely on district-level observations may hinder local goverments to take proper steps; on the other hand, large-scale diversification could still aid regional food security through market assistance, especially when household-level diversification is cost-prohibitive for some smallholders. This highlights the importance of considering scale in crop diversification assessments.

Spatial analysis, as illustrated in Fig. 2(b), indicates that spatial variations in crop diversification are more pronounced than temporal variations. In agriculture year 2018, agro-ecological region (AER) IIa (μ = 0.48) emerges as the most diversified region, while AER I (μ = 0.36) stands out as the least diversified region, with relatively lower crop diversity. The mean diversification level falls within the range of two crop types ([0–0.5]). Furthermore, the majority of households across all AER tend to cultivate fewer than four different crop types, indicating a general trend toward limited diversification. SDI provides a comprehensive measure of crop diversification, but it masks the underlying dynamics. For instance, agro-ecological regions IIb and III, despite presenting similar diversification indices, are characterized by distinct precipitation regimes. This suggests that the same index value can arise from different underlying ecological and economic conditions. Therefore, further analysis is needed to disentangle the contributions of climatic and economic factors to the overall diversification index.

The patterns in SDI over time and space, as shown in Fig. 2, warrant a more nuanced analysis to understand the underlying determinants of SDI. Tables 3 and 4 show that spatial scale changes the regression results for the impact of market characteristics on diversification. We find that, at the district level, road density is statistically significantly positively associated with the SDI. However, the comparable variable 'distance to market' at the household level shows no significant relationship with the SDI. Since we cannot eliminate the endogeneity of market distance/road density with crop diversification, we discuss correlation rather than causation. A possible explanation is that small-scale specialization could still be a result of large-scale diversification. In other words, households might shift from staple to other marketable crops without increasing household diversification, and specializing in different crops at the household level can lead to increased crop diversification at the district level. Surprisingly, there is no statistically significant relationship between the crop diversification index and government maize procurement from the Food Reserve Agency, contradicting our initial expectations. Generally, the regression results indicate that crop diversification in Zambia may be less responsive to market drivers and more influenced by weather.

4.2. Current and historical climate shock and crop diversification

Based on the analysis of drivers of crop diversification at the district-level and household-level in Tables 3 and 4, it is apparent that different climate signals have diverse impacts on crop diversification. As per our definition of weather and climate variables, we intend to assess their impact across three levels:

(1) Current year planting season weather: The influence of high heat stress and severe rainfall deficits during the planting season on crop diversification decisions is complex. The impact of extreme shocks during planting season on district and household behavior may be associated with location-specific factors such as climate, soil conditions, and local crop types, as further discussed in Section 4.3. High heat stress and severe rainfall deficits during the planting season mostly show a positive and statistically significant relationship with crop diversification. Since optimal temperature and adequate water supply are crucial for Zambia's staple crop,

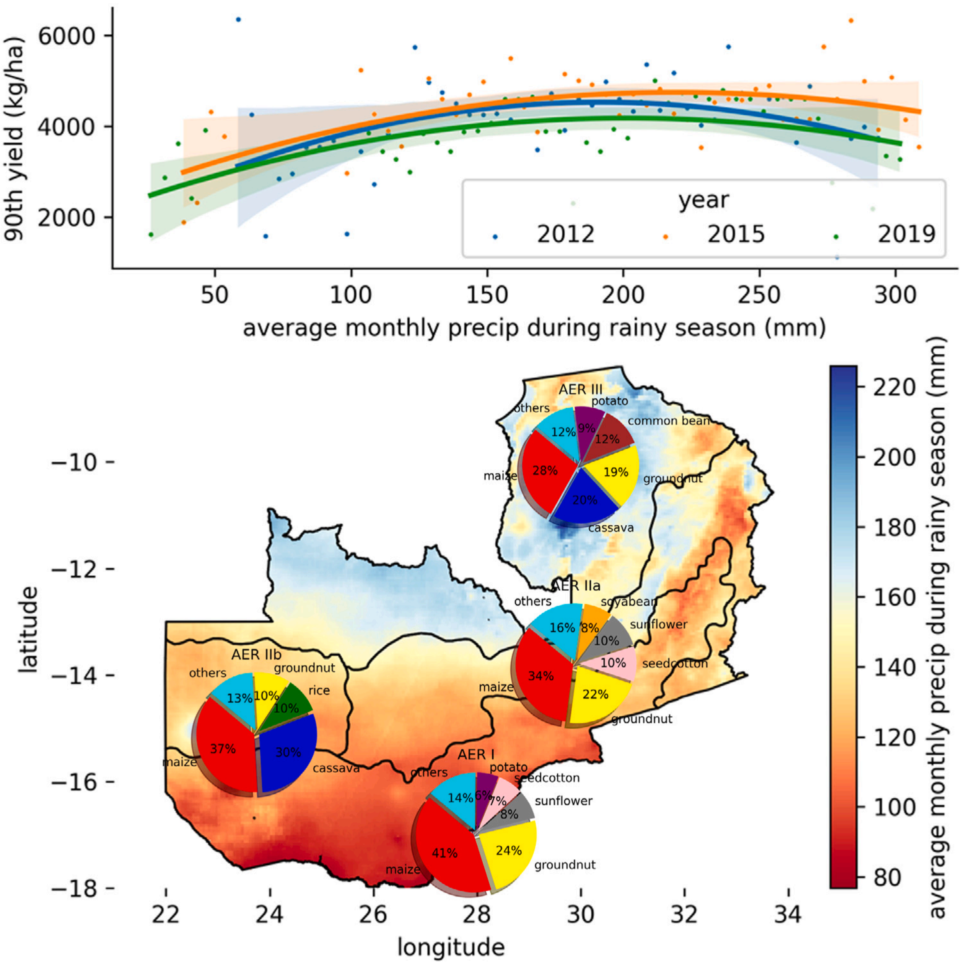

Fig. 3. (a) Household optimal yield data[3] in response to average monthly precipitation during the growing month. (b) The spatial allocation of different crops exhibits notable variations in Zambia. The percentage pie charts represent the distribution of major crops in each Agro-Ecological Region (AER), indicating the proportion of planting area allocated to different crops. Each pie chart shows the share of crops whose average planting area over three years is at least 5% within the respective AER. The colors correspond to different crops, highlighting regional differences in crop selection.
Data source: RALS.

maize, the anticipation of potential climate shocks may encourage farmers to shift to more resilient crops (Miao et al., 2016; Ponce, 2020), such as common beans, that can planted in late December to early January.

(2) Historical climate shocks: The severity of climate shocks during the last three years in crop growing season exhibits a positive association with crop diversification at both household and district levels. Severe climate shocks might pose significant risks to crop yields. When farmers experience these events, they may recognize the need to diversify their crops as a form of risk management. This aligns with findings by Nazir and Lohano (2022), who found that previous crop loss encourages farmer's decision on crop diversification.

(3) In contrast to studies suggesting that greater climate variability promotes crop diversification (Piedra-Bonilla et al., 2020), this study finds that the last 10-year climate variability is unexpectedly not statistically significant in explaining crop diversification in Zambia. This result aligns with findings from Arslan et al. (2018) on crop diversification in Zambia. A possible explanation is that the temporal coverage of the datasets used here may be too limited to fully capture the effects of long-term climate change.

The frequency of extreme climatic events is predicted to increase in the future in Zambia (Kotir, 2011). There will be an increasing need for adaptation to climate risk through crop diversification. It is of great importance how the government and non-profit organizations provides appropriate resources to assist with the transformation.

[3] The y-axis represents the 90th percentile of crop yield within each precipitation bin (step = 5 mm). The utilization of the 90th percentile yield allows for an approximation of the potential optimal yield achievable using the available technology.

4.3. Heterogeneity in drivers of crop diversification in diverse Agro-Ecological Zones

The influence of the location-specific factors like the agro-ecological conditions on crop diversification are emphasized in recent studies (Nazir and Lohano, 2022; Rahman, 2016), Table 5 focus on how different regions (AER I, IIa, IIb, and III) exhibit unique crop adaptations and climate sensitivities based on their environmental characteristics and dominant crops.

The positive association between rainfall deficits and crop diversification in AER I likely stems from the fact that AER I is characterized as the agro-ecological region with the lowest precipitation in Zambia. As inferred from the crop-precipitation relationship depicted in Fig. 3, the response of optimal crop yield to precipitation is nonlinear. Precipitation levels below a certain threshold likely lead to declines in crop yield, even with a variance level similar to that of higher precipitation regions.

The results in AER IIa suggests that farmers diversify when facing heat stress in December. Sunflower, soybean, and groundnuts are typically planted around December. These three crops, having slightly different planting months compared to maize, are the most popular crop substitutes in AER IIa, as illustrated in Fig. 3. Furthermore, experiencing a high heat stress shock in the last three years also contributes to an increase in crop diversification for AER IIa.

The negative association between weather conditions and diversification in AER IIb and III can be explained by the fact that cassava cultivation is prevalent in AER IIb and III. Cassava has a unique ability to be planted at almost any time of the year, as well as a long growth cycle (it can be grown for several years). These biophysical characteristics of cassava mean that short-term climatic conditions less influence it. Hence, growing cassava dampens the link between weather extremes and diversification, since cassava is less susceptible to weather conditions. In other words, even if there are weather extremes, cassava's adaptability reduces the need to diversify across crops.

In summary, the impact of weather and climate shock on crop diversification is significantly influenced by the spatial heterogeneity of climate conditions and the specific properties of the crops involved.

4.4. Limitation and future extension

This study has limitations and areas for improvement. We use three-wave household and nine-year district data to access crop diversification across eleven crops since this is the most reliable data currently available for agriculture decision-making throughout Zambia. However, this limited temporal coverage reduces our ability to capture the impact of a changing climate on diversification practices. In future studies, exploring diversification in more crops and crop varieties, beyond the eleven main crop species cultivated by smallholders in Zambia, would be intriguing. Unfortunately, the available records of other crops and seed varieties in the RALS datasets are sparse, with most crops predominantly relying on local seeds. This study contributes to the existing literature by shedding light on the spatial–temporal variations of crop diversification, as well as the underlying factors influencing diversification dynamics in Zambia. The findings underscore the need for context-specific policies and interventions when promoting agricultural adaptations to climate change.

5. Conclusion

Crop diversification has been identified as an important adaptation measure to climate change and variability in smallholder farming systems. Through a comprehensive analysis of household and district-level data, we examine the impact of current and historical climate shock on crop diversification across different spatial and temporal scales in Zambia. Crops diversification in Zambia has undergone changes over time and across different regions, yet it remains at a generally low level. The observed spatial heterogeneity in crop diversification indicates distinct preferences and adaptation strategies among households in various regions. While there is a slight increase in crop diversification over time, spatial differences are more pronounced. This underscores the importance of considering the region when developing crop diversification strategies in Zambia.

Weather and climate variables, specifically the severity of heat stress and rainfall deficits, are key drivers of crop diversification. High heat stress and rainfall deficits during critical planting months, such as October and December, are positively associated with crop diversification, highlighting farmers' adaptive responses to climate-induced risks. Furthermore, the cumulative effects of climate shocks over the past three years encourage diversification as a long-term resilience strategy, particularly in regions with higher climate variability. However, the impact of these weather variables is not uniform across Zambia. It varies depending on the agro-ecological conditions and crop characteristics in each area. For example, in regions where cassava is a dominant crop, the impact of extreme weather on diversification is reduced, due to cassava's resilience and flexibility in planting regimes. Household demographics were also found to drive crop diversification. Specifically, households with a female head and high dependency rate had less diversification, since those households would have less available labor and social resources to diversify.

Our findings emphasize the importance of considering spatial heterogeneity and scale in understanding agricultural adaptation strategies. While district-level diversification patterns reflect broader regional resilience, household-level analysis reveals more localized vulnerabilities, especially where monoculture remains dominant. Additionally, infrastructure factors like road density positively influence crop diversification at the district level, underscoring the role of market access and transportation in facilitating adaptive practices. Surprisingly, the study does not find a statistically significant relationship between crop diversification and market-related values at the household level.

While our study is conducted within the Zambian context, the underlying findings of crop diversification as a response to environmental stresses such as heat and rainfall shock have universal relevance. The spatial heterogeneity observed across the Zambian agro-ecological regions underscores the importance of localized adaptations in agricultural practices, which can be mirrored in other countries with varied geographical and climatic conditions. Moreover, the drivers of crop diversification identified — such as heat stress and rainfall shortages — are common issues faced by smallholder farmers globally. Therefore, the study on Zambia can inform similar strategic planning and policy-making efforts in other parts of the world.

CRediT authorship contribution statement

Junren Wang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Megan Konar:** Writing – review & editing, Writing – original draft, Conceptualization. **Patrese Nicole Anderson:** Writing – review & editing, Conceptualization. **Protensia Hadunka:** Writing – review & editing, Data curation, Conceptualization. **Brian Mulenga:** Writing – review & editing, Data curation.

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.

Acknowledgments

This material is based upon work supported by the National Science Foundation Grant No. CBET-1844773 ("CAREER: A National Strategy for a Resilient Food Supply Chain"), DEB-1924309 ("CNH2-L: Feedbacks between Urban Food Security and Rural Agricultural Systems"), and CBET-2115405 ("SRS RN: Multiscale RECIPES (Resilient, Equitable, and Circular Innovations with Partnership and Education Synergies) for Sustainable Food Systems"). Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.crm.2024.100683.

Data availability

Data will be made available on request.

References

Acevedo, M., Pixley, K., Zinyengere, N., Meng, S., Tufan, H., Cichy, K., Bizikova, L., Isaacs, K., Ghezzi-Kopel, K., Porciello, J., 2020. A scoping review of adoption of climate-resilient crops by small-scale producers in low-and middle-income countries. Nat. Plants 6 (10), 1231–1241.

Arslan, A., Cavatassi, R., Alfani, F., Mccarthy, N., Lipper, L., Kokwe, M., 2018. Diversification under climate variability as part of a CSA strategy in rural Zambia. J. Develop. Stud. 54 (3), 457–480.

Auffhammer, M., Carleton, T.A., 2018. Regional crop diversity and weather shocks in India. Asian Develop. Rev. 35 (2), 113–130.

Benin, S., Smale, M., Pender, J., Gebremedhin, B., Ehui, S., 2004. The economic determinants of cereal crop diversity on farms in the ethiopian highlands. Agricult. Econ. 31 (2–3), 197–208.

Birthal, P.S., Hazrana, J., 2019. Crop diversification and resilience of agriculture to climatic shocks: Evidence from India. Agricult. Syst. 173, 345–354.

Bozzola, M., Smale, M., 2020. The welfare effects of crop biodiversity as an adaptation to climate shocks in Kenya. World Dev. 135, 105065.

Chibbompa, C.C., 2018. Impact of e-voucher farmer input support programme (FISP) on crop productivity and income diversification among small scale farmers of Lukanda Agricultural Camp in Kapiri Mposhi District in Zambia (Ph.D. thesis). Mulungushi University.

Chikobola, M.M., Tembo, G., 2018. Policy brief gaps in the implementation of the e-voucher system in Zambia: Implications for strategies to make the model efficient and effective. Afr. J. Agricult. Resour. Econom. 13 (311-2018-3124), 193–197.

DataBank, 2023. URL https://databank.worldbank.org/source/jobs [Accessed 19 June 2023].

Davis, K.F., Downs, S., Gephart, J.A., 2021. Towards food supply chain resilience to environmental shocks. Nature Food 2 (1), 54–65.

FAO, 2023. Food balance sheet. https://www.fao.org/faostat/en/#data/FBS [Accessed 26-Apr-2023].

Feres, J.G., Reis, E.J., Speranza, J.S., 2008. Assessing the impact of climate change on the Brazilian agricultural sector.

Fujimoto, T., Suzuki, A., 2025. Different strategies of crop diversification between poor and non-poor farmers: Concepts and evidence from tanzania. Ecol. Econom. 227, 108369.

Fung, W., Liverpool-Tasie, L.S.O., Mason, N.M., Oyelere, R.U., 2020. Do crop purchase programs improve smallholder welfare? The case of Zambia's food reserve agency. Agricult. Econ. 51 (4), 519–533.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2 (1), 1–21.

Goldberg, Z.A., Powell, B., Ouarghidi, A., 2021. Determinants of smallholder maintenance of crop diversity in Morocco's high Atlas Mountains. Hum. Ecol. 49, 453–465.

Hassan, B.A., Knight, J., 2023. Adaptation to climate change and variability by farming households in North-Central Nigeria. Sustainability 15 (23), 16309.

Hersbach, H., 2016. The ERA5 atmospheric reanalysis. In: AGU Fall Meeting Abstracts, vol. 2016. pp. NG33D–01.

Inoni, O.E., Gani, B.S., Sabo, E., 2021. Drivers of crop diversification: evidence from smallholder farmers in delta state Nigeria. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis 69 (1).

International Steering Committee for Global Mapping and Zambia Survey Department, 2012. Districts, Zambia, 2012. [Shapefile]. https://earthworks.stanford.edu/catalog/stanford-vn685gp2885 (Accessed 6 November 2023).

Kaluba, P., Verbist, K., Cornelis, W., Van Ranst, E., 2017. Spatial mapping of drought in Zambia using regional frequency analysis. Hydrol. Sci. J. 62 (11), 1825–1839.

Kotir, J.H., 2011. Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environ. Develop. Sustain. 13, 587–605.

Kumar, S., Kumar, S., Chahal, V.P., Singh, D.R., 2018. Trends and determinants of crop diversification in Uttar Pradesh. Indian J. Agricult. Sci. 88 (11), 1704–1708.

Kurukulasuriya, P., Mendelsohn, R., 2008. Crop switching as a strategy for adapting to climate change. Afr. J. Agricult. Resour. Econom. 2 (311-2016-5522), 105–126.
Labeyrie, V., Renard, D., Aumeeruddy-Thomas, Y., Benyei, P., Caillon, S., Calvet-Mir, L., Carrière, S.M., Demongeot, M., Descamps, E., Junqueira, A.B., et al., 2021. The role of crop diversity in climate change adaptation: Insights from local observations to inform decision making in agriculture. Curr. Opin. Environ. Sustain. 51, 15–23.
Lamptey, S., 2022. Agronomic practices in soil water management for sustainable crop production under rain fed agriculture of Drylands in Sub-Sahara Africa. Afr. J. Agricult. Res. 18 (1), 18–26.
Li, C., Chen, X., Jiang, A., Lee, M.-B., Mammides, C., Goodale, E., 2021. Socioeconomic determinants of crop diversity and its effect on farmer income in guangxi, southern China. Agriculture 11 (4), 336.
Libanda, B., Ngonga, C., 2018. Projection of frequency and intensity of extreme precipitation in Zambia: a CMIP5 study. Clim. Res. 76 (1), 59–72.
Makate, C., Angelsen, A., Holden, S.T., Westengen, O.T., 2023. Evolution of farm-level crop diversification and response to rainfall shocks in smallholder farming: Evidence from Malawi and Tanzania. Ecol. Econom. 205, 107736.
Makondo, C.C., Chola, K., Moonga, B., et al., 2014. Climate change adaptation and vulnerability: A case of rain dependent small-holder farmers in selected districts in Zambia. Amer. J. Clima. Change 3 (04), 388.
Miao, R., Khanna, M., Huang, H., 2016. Responsiveness of crop yield and acreage to prices and climate. Amer. J. Agricult. Econom. 98 (1), 191–211.
Mofya-Mukuka, R., Hichaambwa, M., 2018. Livelihood effects of crop diversification: a panel data analysis of rural farm households in Zambia. Food Secur. 10 (6), 1449–1462.
Nahar, N., Rahman, M.W., Miah, M.M., Hasan, M.M., 2024. The impact of crop diversification on food security of farmers in Northern Bangladesh. Agricult. Food Secur. 13 (1), 9.
Nazir, A., Lohano, H.D., 2022. Resilience through crop diversification in Pakistan. Clim. Change Commun Resil. 431–442.
Niles, M.T., Salerno, J.D., 2018. A cross-country analysis of climate shocks and smallholder food insecurity. PLoS One 13 (2), e0192928.
Papke, L.E., Wooldridge, J.M., 2008. Panel data methods for fractional response variables with an application to test pass rates. J. Econometrics 145 (1–2), 121–133.
Piedra-Bonilla, E.B., da Cunha, D.A., Braga, M.J., 2020. Climate variability and crop diversification in Brazil: An ordered probit analysis. J. Clean. Prod. 256, 120252.
Ponce, C., 2020. Intra-seasonal climate variability and crop diversification strategies in the Peruvian Andes: A word of caution on the sustainability of adaptation to climate change. World Dev. 127, 104740.
Rahman, S., 2016. Impacts of climate change, agroecology and socio-economic factors on agricultural land use diversity in Bangladesh (1948–2008). Land Use Policy 50, 169–178.
Rahman, S., Kazal, M.M.H., 2015. Determinants of crop diversity in the regions of Bangladesh (1990–2008). Singapore J. Trop. Geograph. 36 (1), 83–97.
Salazar-Espinoza, C., Jones, S., Tarp, F., 2015. Weather shocks and cropland decisions in rural Mozambique. Food Policy 53, 9–21.
Schlenker, W., Roberts, M.J., 2006. Nonlinear effects of weather on corn yields. Rev. Agricult. Econom. 28 (3), 391–398.
Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proc. Natl Acad. Sci. 106 (37), 15594–15598.
Seo, S.N., 2010. A microeconometric analysis of adapting portfolios to climate change: adoption of agricultural systems in Latin America. Appl. Econom. Perspect. Policy 32 (3), 489–514.
Seo, S.N., Mendelsohn, R., 2008. An analysis of crop choice: Adapting to climate change in South American farms. Ecol. Econom. 67 (1), 109–116.
Shezongo-Macmillan, J., 2005. Women's property rights in Zambia. In: Strategic Litigation Workshop, Johannesburg, South Africa, August. pp. 14–18.
Siatwiinda, S.M., Supit, I., van Hove, B., Yerokun, O., Ros, G.H., de Vries, W., 2021. Climate change impacts on rainfed maize yields in Zambia under conventional and optimized crop management. Clim. Change 167, 1–23.
Thierfelder, C., Mhlanga, B., 2022. Short-term yield gains or long-term sustainability?–a synthesis of Conservation Agriculture long-term experiments in Southern Africa. Agricult. Ecosyst. Environ. 326, 107812.
Wheeler, T., Von Braun, J., 2013. Climate change impacts on global food security. Science 341 (6145), 508–513.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.
Zougmoré, R.B., Partey, S.T., Ouédraogo, M., Torquebiau, E., Campbell, B.M., 2018. Facing climate variability in sub-Saharan Africa: analysis of climate-smart agriculture opportunities to manage climate-related risks. Cahiers Agricult. (TSI) 27 (3), 1–9.