Agricultural Systems 173 (2019) 345–354

Contents lists available at ScienceDirect

Agricultural Systems

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

Crop diversification and resilience of agriculture to climatic shocks: Evidence from India

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ARTICLE INFO

Keywords:
Rainfall-deficit
Heat-stress
Agriculture
Diversification
Resilience

ABSTRACT

Indian agriculture is highly vulnerable to climate shocks, such as floods, droughts and heat-stress. In this paper, using a dynamic panel-data approach we have assessed the impact of rainfall-deficit and heat-stress on agricultural productivity, and subsequently evaluated effectiveness of crop diversification in mitigating their adverse effects. The findings show that both rainfall-deficit and heat-stress damage agricultural productivity, and the damage increases with increase in their severity. Nevertheless, we find crop diversification as an important *ex ante* adaptation measure to climatic shocks and its adaptation benefits are more apparent against severe shocks and in the long-run. Our findings reinforce the dynamic role of crop diversification in improving resilience of agricultural production systems to climatic shocks.

1. Introduction

Globally, climate change has become a big threat to sustainable development of agriculture and agriculture-based livelihoods. The threat is more conspicuous in the case of extreme changes in climate, manifested as droughts, floods, heat-waves and cyclones. Frequent occurrence of such extreme events adversely affects agricultural productivity and food supplies, causes loss to productive assets (e.g., livestock), exacerbates rural poverty, forces out-migration, reduces demand for industrial goods and services, and triggers over-exploitation of natural resources i.e., water, land and forests.

The frequency of extreme climatic events has increased in the recent past, and is predicted to rise in the plausible future scenario (World Bank, 2013). The developing countries, as India, are more vulnerable to climatic shocks because of their greater dependence on agriculture, small landholdings and lack of financial resources, technologies, infrastructure and institutions to cope with such shocks. Carter et al. (2014) observe that in developing countries, farmers' frequent exposure to climatic shocks is one of the major causes of low agricultural productivity, slow economic growth and persistent poverty. Bhandari et al. (2007) provide an evidence from India that in case of a severe drought the household incomes fall by 25–60% and incidence of poverty rises by 12–33%. Likewise, from a study in Nigeria, rainfall shocks have been reported to reduce agricultural productivity by 42% and household consumption by 38%, and the impact being larger on the asset-poor households (Amare et al., 2018). Bhandari et al. (2007) and Amare et al. (2018) have further noticed that despite the use of several risk-coping mechanisms, farm households were unable to recover the loss of assets *ex post* the shock.

It is, however, increasingly recognized that the adverse effects of climate change on agriculture can be minimized following an integrated approach encompassing advancements in the science of agriculture, meteorology and information communication, and traditional adaptation practices that farmers use *ex ante* and *ex post* the shock. Farmers, depending on their degree of risk-aversion, access to information on weather and availability of resources for their adoption, undertake a number of adaptation measures to cope with production risks. Risk-averse farmers, who anticipate occurrence of a shock, often rely on *ex ante* risk management strategies, such as building of savings, diversification towards non-farm activities and choosing a less risky crop portfolio, to achieve a stable stream of income.

There are two important channels through which climatic shocks impact agriculture. One, climatic shocks influence farmers' decisions to adopt productivity-enhancing inputs and impose *ex ante* barriers to their use, that in turn affect agricultural productivity (Dercon and Christiaensen, 2011; Di Falco and Chavas, 2009; Amare et al., 2018). Two, they reinforce changes in production portfolio towards crops or their varieties that are less-vulnerable to climatic shocks, but at the same time these crops may also be less remunerative compared to others. Crops differ in their response to climatic shocks, and the risk-averse farmers prefer choosing a combination of crops with low-correlated returns to spread risks across crops. If a crop does not perform

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https://doi.org/10.1016/j.agsy.2019.03.005
Received 25 October 2018; Received in revised form 31 January 2019; Accepted 9 March 2019
Available online 22 March 2019
0308-521X/

well under risk, the loss, to an extent, can be compensated by the gains in another crop that withstands the risk better. The literature shows that in developing countries, where formal markets for risk products are under-developed, crop diversification is one of the widely used *ex ante* adaptation measures to cope with climatic shocks (Jodha, 1981; Bromley and Chavas, 1989; Rosenzweig and Binswanger, 1993; Dercon, 1996; Valdivia et al., 1996; Di Falco and Chavas, 2009; Seo and Mendelsohn, 2008; Seo, 2010; Macours et al., 2012).

Indian agriculture being rain-dependent is highly exposed to climatic shocks (Easterling et al., 2007). About 45% of the total cropped area in the country is rainfed, and the evidence shows that rainfed production systems are more vulnerable to rainfall and temperature shocks (Birthal et al., 2014). Note, the frequency of climatic shocks in India has increased in the recent past and is predicted to rise in the future (World Bank, 2013), that will accentuate their adverse effects on agriculture and agriculture-based livelihoods in the absence of adaptations. A majority of Indian farmers are small landholders,[1] who are often risk-averse and lack resources to invest in costlier adaptations to cope with risk *ex ante*. For most farmers, crop diversification is one of the low-cost, effective adaptations to avoid productivity loss due to climatic shocks.

Using a panel of district-level data, this paper evaluates effectiveness of crop diversification in mitigating harmful effects of climatic shocks on the performance of agriculture in a dynamic setting. In doing so it makes an important contribution to the empirical literature in understanding the dynamics of agricultural production systems. Although there are several studies that examine the effect of crop diversification on agriculture in the presence of climatic shocks, but most of these apply static modelling approaches, ignoring the dynamic relationships that exist in the production systems. Farmers' current year decisions on the choice of crop portfolio and input-use are influenced not only by the anticipated weather conditions but also by their past experiences. We model this dynamic aspect of production systems by estimating a dynamic generalized method of moments (GMM) with lags of dependent and independent variables as instruments. This approach also addresses the issue of potential endogeniety of the explanatory variables.

Our results show that (i) there is a dynamic relationship among climate shocks, crop diversification and agricultural productivity, and (ii) diversification enhances resilience of agricultural production systems to climatic shocks, and its adaptation benefits are more apparent in the long-run. It may be noted that our findings reflect aggregate response of farmers to climatic shocks at district-level, although the farmer-specific responses vary within and across districts due to heterogeneity in their socio-economic conditions, and access to technologies, inputs and information that shape their attitude towards risk and risk management strategies.

Rest of the paper is organized as follows. Section 2 describes the method that we have employed to assess adaptation benefits of crop diversification in the presence of climatic shocks. In Section 3, we provide a brief discussion on data sources, and preliminary analysis of the relationship among climatic shocks, agricultural productivity and crop diversification. Econometric results are discussed in Section 4, and concluding remarks are made in the final section.

2. Empirical method

Several methods are used to quantify the impact of climatic shocks on crop yields or productivity of agricultural system. In the simplest form, the impact of a climatic shock can be assessed by regressing crop yield or agricultural productivity on climate variables (Cabas et al., 2010; Kaufmann and Snell, 1997; Mendelsohn and Dinar, 1999; Lobell and Asner, 2003). 'Value at risk' is the other approach that is widely used to estimate climate-induced loss in agriculture as the product of (i) the probability of occurrence of a climatic shock; (ii) the value of crop exposed to the shock, and (iii) the vulnerability of crop to the shock (see ECA, 2009 for details).

Di Falco and Chavas (2008) argue that these approaches are static approaches and neglect the dynamic behaviour of production systems and the problem of endogeneity of explanatory variables. They suggest the use of dynamic panel-data approach that takes care of the system dynamics and endogeneity.

Following Di Falco and Chavas (2008), we specify a static production function $y_{it} = f_{it}(\boldsymbol{x_{it}})$; where, y_{it} is agricultural or system productivity at location $\boldsymbol{i}$ (in our case district) at time t; and x_{it} is a vector of conventional inputs (i.e., labour, capital, animal labour, fertilizer and irrigation). Agricultural productivity (y_{it}) is measured in monetary terms as the 'value of output of crops per unit of cropped land'. All the explanatory variables (except irrigation) are expressed per unit of land. Irrigation is expressed as proportion of the cropped area.

To make the production function dynamic, we include k^{th} lags of y_{it} and x_{it}, and re-write it as: $y_{it} = f_{it}(\boldsymbol{x_{it}}; y_{i,\,t-1}, \dots, y_{i,\,t-p}, x_{i,\,t-1}, \dots, x_{i,\,t-q})$ for $p \geq 0$ and $q \geq 0$. For estimation purpose, we specify it as:

$$\ln(y_{it}) = \boldsymbol{A} + \boldsymbol{\alpha}\, ln(\boldsymbol{x_{it}}) + \sum\nolimits_{k=1}^{p} \beta_k \ln(y_{i,t-k}) + \sum\nolimits_{k=1}^{q} \boldsymbol{\eta_k} \ln(x_{i,t-k}) + \mu_t + \nu_{it} \tag{1}$$

where, $\boldsymbol{\alpha}$ and $\boldsymbol{\eta_k}$ represent the parameter vectors associated with current ($\boldsymbol{x_{it}}$) and lagged inputs ($x_{i,\,t-k}$), respectively; and β_k is the parameter of k^{th} lagged dependent variable (y_i). μ_t represents the district-specific effects and ν_{it} is the time- and district-varying residual disturbance. μ_t and ν_{it} are independently distributed with zero mean and finite variance.

The main aim of this paper is to assess the dynamic effects of crop diversification on resilience of agriculture in the presence of climatic shocks; hence we extend Eq. (1) to include: (i) climate shocks i.e., rainfall-deficit and heat-stress, and their lags, (ii) index of crop diversification and its lags, and (iii) interaction of diversification with climatic shocks in the current and previous year(s).

$$\begin{aligned}\ln(y_{it}) = {} & \boldsymbol{A} + \boldsymbol{\alpha}\, ln(\boldsymbol{x_{it}}) + \sum\nolimits_{k=1}^{p} \beta_k \ln(y_{i,t-k}) + \sum\nolimits_{k=1}^{q} \boldsymbol{\eta_k} \ln(x_{i,t-k}) \\ & + \rho_0(SID_{it} * RD_{it}) + \rho_1(SID_{it} * RD_{i,t-1}) + \lambda_0(SID_{it} * HS_{it}) \\ & + \lambda_1(SID_{it} * HS_{i,t-1}) + \mu_t + \nu_{it}\end{aligned} \tag{2}$$

In Eq. (2), RD and HS represent the rainfall-deficit and heat-stress, respectively, and SID is the index of crop diversification.

We define rainfall-deficit as the standardized deviation of annual rainfall from its long-term mean so as to make it comparable over time and space. For each district, we subtract the long-term mean of annual rainfall (mm) from the annual rainfall and divide it by its standard deviation. Mathematically, it can be expressed as: $RD_{it} = \frac{RAIN_{it} - \overline{RAIN_i}}{\sqrt{E\,[(RAIN_{it} - \overline{RAIN_i})^2]}}$. As our variable of interest is rainfall-deficit, we retain only negative deviations in rainfall in our econometric model.

Defining heat-stress is complex. There is no universal threshold beyond which a rise in temperature can be termed as heat-stress or heat-wave. In its fifth annual assessment report, the Intergovernmental Panel on Climate Change (IPCC) defines heat-wave 'as a period of abnormally high temperatures causing discomfort' (IPCC, 2012). For agricultural purposes, Lipiec et al. (2013) define heat-stress as 'the rise in temperature beyond a threshold continuously for a period sufficient to cause damage to plant growth'. These definitions are too general to identify a heat event precisely.

Several studies have used crop- and location-specific fixed temperature thresholds to define heat-stress and to quantify its effect on crop yields (Rosenzweig et al., 2001; Hawkins et al., 2013; Lobell et al., 2012). A major limitation of this approach is that it does not account for the spatial heterogeneity in agro-climatic conditions (Massetti and

[1] Over two-thirds of farm households in India possess landholdings measuring less than or equal to one hectare.

Mendelsohn, 2015) that in a large country, as India, could be significant even for the same crop grown at different locations.

We follow the criteria by the India Meteorological Department (IMD) of the Government of India to identify heat-stress. IMD defines heat-wave if the daily maximum temperature at a location (in our case district) remains at least 3 °C higher over its long-term mean consecutively for three or more days. Mathematically, it can be expressed as: $(MaxTemp_{di} - MeanTemp_{dit}) \geq 3^{\circ}C$ for ≥ 3 consecutive days. The $MaxTemp_{di}$ and $MeanTemp_{dit}$ are respectively the daily maximum and daily mean temperatures, with subscript d representing the day, i the district, and t the time.

To measure diversity in cropping system, we construct Simpson index of diversification (SID) that takes into account the number of crops in the portfolio as well as their relative shares in the portfolio. It is written as: $SID = 1 - \Sigma p_i^2$, where, p_i is the area share of crop i in the total cropped area. The index is bounded by zero and one; zero implies complete specialization and one implies complete diversification.

The panel-data specification of Eq. (2) controls for cross-section heterogeneity (Baltagi, 2001), improves efficiency of parameters and provides a basis to study the short-run as well as the long-run dynamic effects of dependent and independent variables. We transform variables in Eq. (2) into their first-difference so as to eliminate individual effects and to reduce serial correlation (Baltagi, 2001).

$$\begin{aligned}\Delta \ln(y_{it}) = \alpha \Delta\, ln(x_{it}) + \sum\nolimits_{k=1}^{p} \beta_k \Delta \ln(y_{i,t-k}) + \sum\nolimits_{k=1}^{q} \boldsymbol{\eta}_{\mathbf{k}} \Delta \ln(x_{i,t-k}) \\ + \rho_0 \Delta(SID_{it} * RD_{it}) + \rho_1 \Delta(SID_{it} * RD_{i,t-1}) \\ + \lambda_0\, \Delta(SID_{it} * HS_{it}) + \lambda_1 \Delta(SID_{it} * HS_{i,t-1}) + \Delta \nu_{it}\end{aligned} \tag{3}$$

Eq. (3) includes lags of the dependent variable as regressors that are correlated with the error term. This violates the assumption of strict exogeneity, and renders application of static panel data techniques (e.g., fixed effects) inconsistent. We, therefore, estimate Eq. (3) using generalized method of moments (GMM), which when some of the explanatory variables are endogenous, generates consistent parameter estimates. Further, if the error terms are serially uncorrelated, then the lags of dependent variable serve as valid instruments (Arellano and Bond, 1991) and GMM provides asymptotically efficient parameter estimates. The Arellano–Bond estimation uses GMM and transforms all regressors by differencing them (Hansen, 1982). The Arellano–Bover/Blundell–Bond estimator additionally assumes that first differences of instrumental variables are uncorrelated with fixed effects. This assumption augments the Arellano–Bond estimator and allows introduction of more instruments in the model that may improve efficiency of the parameters. This method builds a system of two equations (original equation and transformed equation), and is known as system GMM. Both the Arellano and Bond GMM and the system GMM are used in empirical studies, we, however, use system GMM as it provided us significant efficiency gains.

3. Data and descriptive statistics

3.1. Data sources

We have used data from two main sources. The data on area, crop output, and inputs used (fertilizers, irrigation, agricultural workers, draught animals and tractors) for the period 1966 to 2011 on 311 districts at their 1970 boundaries have been extracted from the database maintained by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, India (http://vdsa.icrisat.ac.in/vdsa-database.htm). This data-set is used to estimate diversity and productivity of the system. Agricultural productivity is measured as the sum of monetary values of crop outputs (at 2004–05 prices) divided by the sum of area under crops. The crops include cereals (rice, wheat, maize, sorghum, pearl millet, finger millet and barley), pulses (chickpea, pigeon-pea and other pulses), oilseeds (soybean, sesame, groundnut, rapeseed-mustard, groundnut, sunflower, safflower, linseed, and castor), cotton and sugarcane. This data-set also contains information on area of horticultural and plantation crops but not on their outputs, yields and prices; hence we exclude these crops from our analysis.

Table 1
Summary statistics.

Variables	Description	Mean	SD
Ln Agricultural productivity	Rupees/ha	9.299	0.834
Ln Human labour	No. of workers/ha	5.971	0.970
Ln Fertilizers (NPK)	Kg/ha	5.951	1.583
Ln Tractors	No./ha	3.073	2.032
Ln Draught animals	No./ha	5.971	1.014
Irrigation	Proportion of total cropped area irrigated	0.345	0.271
Simpson index of diversity		0.639	0.209
Rainfall-deficit	Standardized deviation of annual rainfall from its long-term mean	0.389	0.525
Heat-stress	Proportion of days in a year	0.038	0.040

To quantify rainfall-deficit and heat-stress, we rely on daily gridded data on rainfall and temperature acquired from the India Meteorological Department, Government of India.

Means and standard deviations of the log-transformed variables used for estimation of Eq. 3 are given in Table 1.

In Fig. 1 we show geographical distribution of rainfall-deficit, heat-stress and diversification index, categorised as low, medium and high in relation to their respective median values.[2] From this we find that (i) the rainfall-shocks are widely spread across districts, (ii) the districts more prone to rainfall shocks have a more diversified crop portfolio, and (iii) the heat-stress is largely concentrated in north-western region, where crop portfolio is not much diversified.

3.2. Descriptive analysis

In Fig. 2 we show distribution of climatic shocks during 1996–2011, and find that the distribution of both the rainfall-deficit and heat-stress is skewed towards their lower bounds. This implies that the probability of occurrence of extreme climatic events, rainfall-deficit as well as heat-stress, is low.

Further, based on their dispersion, we classify climatic shocks as: low, moderate and severe shocks. A shock is of low severity if it is one standard deviation below its mean; moderately severe if it is within ± 1 standard deviation around its mean; and highly severe if it is above one standard deviation of its mean. In Table 2 we present distribution of rainfall-deficit and heat-stress by their severity levels. Of the total rainfall shocks, about two-thirds are moderate, and the low and high rainfall shocks comprise 16% and 17% of these, respectively. Likewise, over 72% of the heat events are moderately severe, and only 15% are of high intensity.

To have an idea about their potential impacts on agriculture, we regress agricultural productivity on rainfall-deficit and heat-stress separately, controlling for the district fixed effects. The coefficient on rainfall-deficit as well heat-stress is negative and significant, indicating that climatic shocks adversely affect agricultural productivity. However, an analysis by their severity level suggests that the low intensity shocks do not cause any damage to agriculture, but the moderate and severe shocks do reduce agricultural productivity (Table 3).

We probe the relationship between climatic shocks and agricultural productivity further by fitting Locally Weighted Scatterplot Smoothing

[2] Rainfall-deficit is presented as standardized deviations; heat-stress is in number of days, and diversification is the index value.

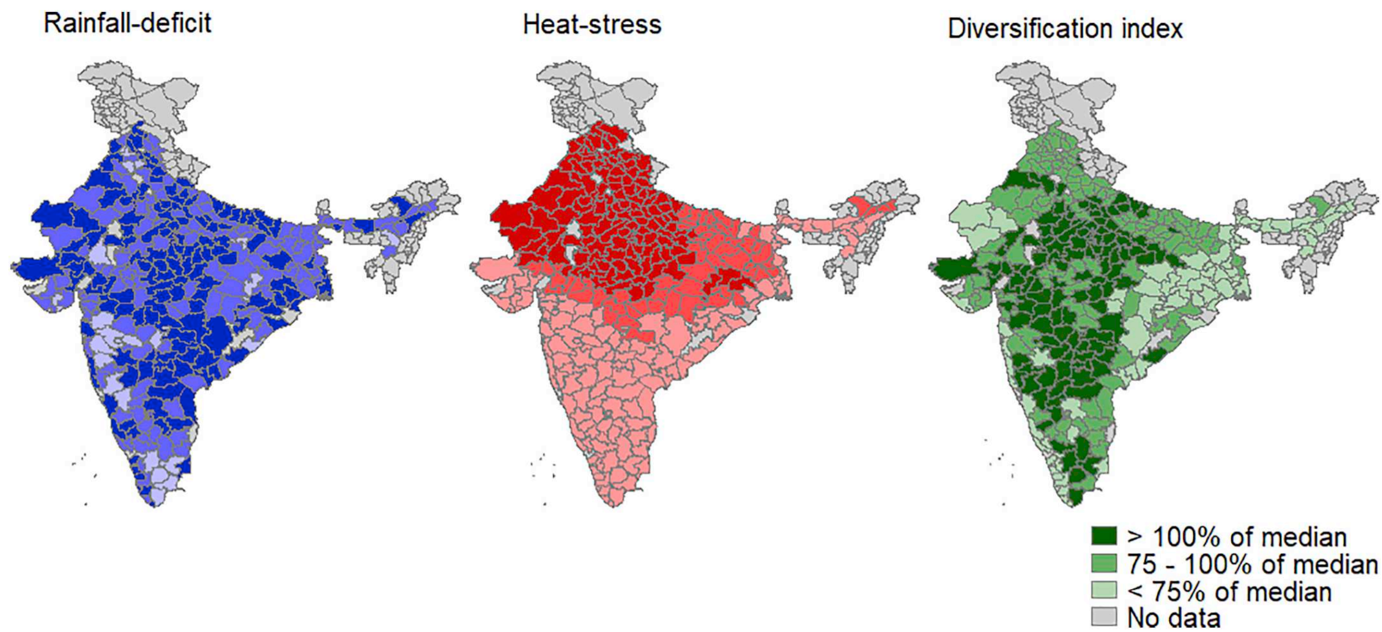

Fig. 1. Distribution of rainfall-deficit, heat-stress days and diversification index during 1966–2011.

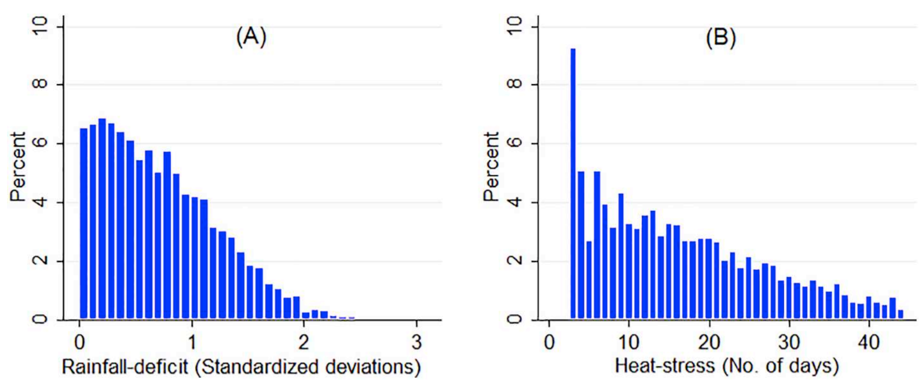

Fig. 2. Frequency distribution of rainfall deficit and heat-stressed days.

Table 2
Distribution of climatic shocks by their severity level.

	Low	Medium	Severe	All
Rainfall-deficit				
Mean	0.122	0.661	1.564	0.732
	(0.002)	(0.004)	(0.001)	(0.060)
% of total	16.02	66.62	17.37	100
Heat-stress				
Mean	5.012	16.28	40.58	18.64
	(0.062)	(0.106)	(0.349)	(0.136)
% of total	12.48	72.03	15.48	100

Robust standard errors are in parentheses.

(LOWESS) and linear splines on the binned scatterplots (100 bins) (Fig. 3). Both the LOWESS and linear splines corroborate the finding that rainfall-deficit and heat-stress damage agricultural productivity and the damage increases with an increase in their severity.

Diversification is an *ex ante* adaptation measure to avoid crop loss due to climatic shocks. Hence, a farmer's decision on the choice of crop portfolio depends on occurrence of climatic shocks during the sowing period. The question is then: Do farmers respond to climatic shocks by diversifying their crop portfolio?

Before we proceed on this issue, we look at dispersion of growth in diversification index across districts during 1966–2011. For the purpose, we plot annual growth in diversification index of all districts (Fig. 4) and find that the growth is highly dispersed, with some districts experiencing positive and others negative trend in diversification.

Now to know whether diversification is an *ex ante* response to climatic shocks, we regress diversification index on rainfall-deficit and heat-stress during the sowing period. There are two main crop seasons in India viz., Kharif (June–September) and Rabi (October–March). We include rainfall-deficit and heat-stress in June for Kharif season, and September for Rabi season in our regressions, controlling for irrigation (which is one of the best adaptations to climate shocks) and district fixed effects. Our choice for September (rather October) for Rabi sowing period is guided by seasonal distribution of rainfall. India receives around 85% of the annual rainfall during Kharif season. Rainfall in October is rare, and several Rabi crops are sown on residual soil moisture due to rainfall in September.

Table 4 presents regression results. For the overall pool of districts, diversification is positively associated with rainfall-deficit as well as heat-stress during Kharif sowing period (i.e., June), and the association is statistically significant. However, the coefficient on heat-stress during Rabi sowing period (i.e. September) is positive, and that on rainfall-deficit it is negative. On the other hand, the relationship between diversification and irrigation is negative and statistically significant, implying that higher level of irrigation discourages farmers to diversify their crop portfolio for risk management. These results are as expected. During 1966–2011, on an average about 22% of the Kharif cropped

Table 3
Effects of climatic shocks on agricultural productivity.

	Rainfall-deficit				Heat-stress			
	Low	Medium	High	All	Low	Medium	High	All
Climatic shocks	0.028	−0.0716***	0.221***	−0.131***	0.058***	−0.018***	−0.055***	−0.044***
	(0.013)	(0.011)	(0.021)	(0.013)	(0.012)	(0.008)	(0.149)	(0.011)
R-Square	0.002	0.006	0.006	0.002	0.0424	0.068	0.019	0.0424
F test	105.7***	47.9***	46.5***	105.7	15.6***	22.5***	4.8***	15.6***

Robust standard errors are in parentheses.
Significance level: * p < .10, ** p < .05, *** p < .01.

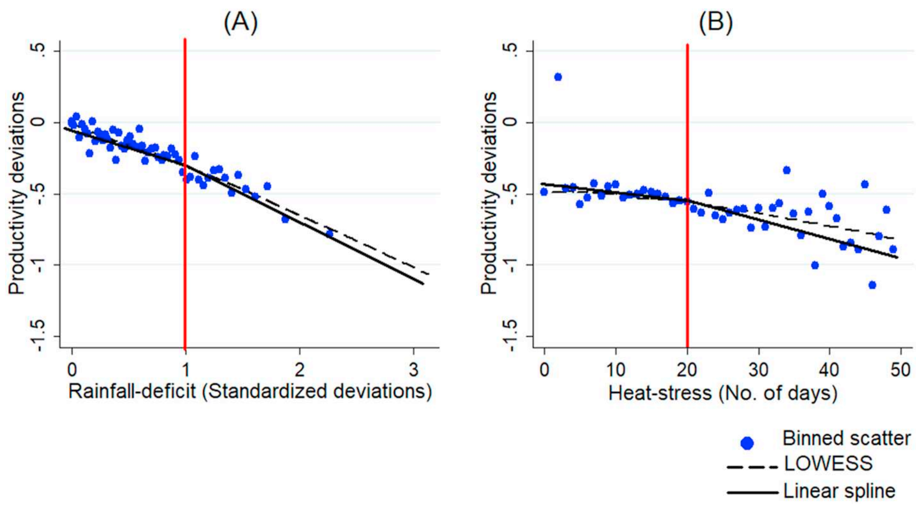

Fig. 3. Binned scatterplot of climatic shocks and productivity deviations.

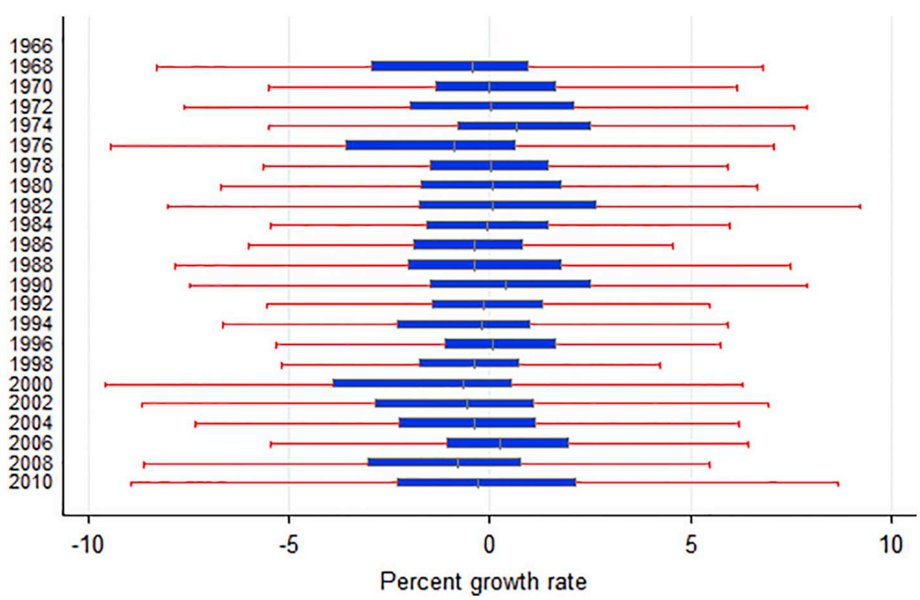

Fig. 4. Dispersion of annual growth in diversification index.

area was irrigated, but largely restricted to rice (41%), the main crop of this season. Several Rabi crops, such as chickpea, rapeseed-mustard and barley are largely sown on residual soil moisture. During this period, 55% of the total Rabi cropped area received irrigation, with wheat as the main beneficiary (78%).

We also regressed seasonal diversification indices on seasonal sowing period climatic shocks. In Kharif season equation, the coefficients on rainfall-deficit as well as heat-stress have the expected signs and are statistically significant. In Rabi season equation, the coefficient on heat-stress remains positive and significant, but the coefficient on rainfall-deficit turns out to be negative but insignificant. In both the seasons, diversification is negatively associated with irrigation. These findings clearly show that climatic shocks during the sowing period sinduce farmers to diversify their crop portfolio towards crops that can tolerate these better.

Next, to see whether crop diversification cushions agricultural productivity against climatic shocks, we plot these at two levels of diversification: below 50% and above 50% of the mean diversification

Table 4
Effects of climatic shocks by season on the diversification index.

	SID (Overall)	SID (Kharif)	SID (Rabi)
Rainfall-deficit (June)	0.0034***	0.0006***	–
	(0.0014)	(0.0016)	
Rainfall-deficit (September)	−0.0017***	–	−0.0056
	(0.0011)		(0.0022)
Heat-stress (June)	0.0141***	0.0108***	–
	(0.0037)	(0.0056)	
Heat-stress (September)	0.0003***	–	0.0047***
	(0.0055)		(0.0099)
Irrigation (Kharif)	−0.0126***	−0.0102***	–
	(0.0106)	(0.0059)	
Irrigation (Rabi)	−0.0153***	–	−0.0147***
	(0.0054)		(0.0091)
R-square	0.0147	0.024	0.0793
F-test	8.08***	2.25*	2.78**

Figures in parentheses are robust standard errors.
Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$.

index (Fig. 5). The association between agricultural productivity and climatic shocks (rainfall-deficit as well as heat-stress) is negative at low-level of diversification. At higher level of diversification, the effects of climatic shocks on agricultural productivity remain negative, but are not as prominent.

These preliminary evidences provide a sound basis for econometric analysis of the dynamic relationship among climatic shocks, agricultural productivity and system diversification that we undertake in the following section.

4. Results and discussion

We estimate Eq. (3) applying system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2009). In our production function, we consider conventional inputs (labour, fertilizers, tractors, draught animals and irrigation) as pre-determined, ($E[x_{it}\epsilon_{is}] \neq 0$ for $s < t$ but $E[x_{it}\epsilon_{is}] = 0$ for all $s > t$); lags of dependent variable, and diversification as endogenous, ($E[x_{it}\epsilon_{is}] \neq 0$ for all $s \leq t$ but $E[x_{it}\epsilon_{is}] = 0$ for all $s > t$); and climatic shocks as strictly exogenous, ($E[x_{it}\epsilon_{is}] = 0$ for all t and s).[3] We include two lags of the dependent variable ($p = 2$) and one lag of the independent variables ($q = 1$).

The endogeniety of diversification index is tested through Davidson and MacKinnon (1993) and Wooldridge (2002) tests using its lags as instruments. These tests reject the null hypothesis of exogeneity of diversification (at 5% level of significance), and suggest the need to correct for endogeneity bias using instrumental variable approach.

The absence of correlation in errors term is a pre-requisite to obtain consistent estimates from a dynamic panel-data model (Cameron and Trivedi, 2009). Following Arellano and Bond (1991), we test whether $\Delta\nu_{it}$ shows second-order serial correlation. The test statistic z equals 0.89 with an associated *p*-value of 0.374; hence, the null hypothesis of second-order serial correlation in error term cannot be rejected. However, there is a possibility that in endogenous models the second-order serial autocorrelation may arise if the instruments are not consistent. We conduct the Sargan-Hansen test on the null hypothesis that instrumental variables are uncorrelated with residuals, a key assumption to support consistency of the GMM estimator. The null hypothesis is not rejected, and our instruments satisfy the orthogonality conditions required for estimation of GMM.

Econometric estimates of Eq. (3) are reported in Table 5. The direction of coefficients on conventional inputs, i.e., fertilizer, animal labour and irrigation in the current year are as expected. The positive and significant coefficients on fertilizer and irrigation clearly confirm their role in improving system productivity. The coefficient on human labour and tractors are negative but not significant. The coefficient on draught animal power is also not significant. However, the coefficients on the lags of almost all the explanatory variables are statistically significant that clearly indicate their dynamic role in the functioning of agricultural production systems. Importantly, the coefficients on both the lags of agricultural productivity are positive and highly significant, suggesting that current level of productivity is positively influenced by its past levels.

Our main interest is to assess the effect of crop diversification on agricultural productivity in the presence of climatic shocks. The coefficient on rainfall-deficit as well as heat-stress is negative, but it is significant only for rainfall shocks, indicating the centrality of rainfall in determining agricultural productivity. Agricultural productivity is positively related to the current year irrigation level, but not to its lag. Similarly, the coefficient on current year diversification index is positive and highly significant, but it is negative and significant on its lag. The negative coefficient on the lagged diversification could be on account of several factors, such as the changes in farmers' perceptions towards risk and their lackadaisical approach to other *ex ante* adaptation measures, *ex post* the diversification. Likewise, the negative coefficient on the lag of irrigation could be due to the less use of other adaptation measures, complementary to irrigation. From Table 4 we noticed a trade-off between irrigation and diversification, and we expect a similar trade off between irrigation (or diversification) and other adaptation measures.

Further, we allow diversification to interact with climatic shocks to know about its potential in improving resilience of agriculture to climatic shocks. Its interaction with the current as well as lagged rainfall-deficit is positive and significant, suggesting that diversification cushions agriculture against rainfall shocks. On the other hand, its interaction with heat-stress in the current year is negative but insignificant, while it is positive and significant with its lag. This is plausible as heat-stress in the previous year could have motivated farmers to diversify their crop portfolio in the subsequent period.

Since most of the rainfall in India occurs during Kharif season, we estimate Eq. (3) separately for Kharif and Rabi seasons. In Kharif season regression, most of the explanatory variables retain their signs and also significance. Only the interactions of diversification with current year heat-stress and lagged rainfall-deficit switch signs. Its interaction with heat-stress is not significant in Kharif season regression. However, the interaction of diversification and lagged rainfall-deficit is negative and significant. On the other hand, in Rabi season regression, most explanatory variables have expected signs but are not significant. These season-specific results indicate that crop diversification is a more important adaptation measure against Kharif season climatic shocks.

These results are suggestive of the relevance of diversification as an adaptation to climatic shocks. To know its true impact, we estimate marginal effects of rainfall-deficit, heat-stress and diversification (Table 6). Evaluated at their means, the marginal effects of rainfall-deficit and heat-stress are negative and significant confirming that climatic shocks reduce agricultural productivity, and the effects get accentuated in the long-run. On the other hand, the marginal effect of diversification is positive and significant and its adaptation benefits are larger in the long-run.

The marginal effects of climatic shocks as well as diversification vary across crop seasons. In Kharif season, the marginal effects of rainfall-deficit, heat-stress and diversification are as expected. In Rabi season, the short-run marginal effects of climatic shocks and diversification are not significant. However, the long-run marginal effects of rainfall-deficit and diversification are as expected, but not that of heat-stress. The positive long-run effect of heat-stress on agricultural productivity is contrary to our expectations. Note, the effect of heat-stress on agriculture has remained less researched (Deryng et al., 2014), and

[3] The endogenous variables differ from the predetermined variables as the former allow for correlation between x_{it} and ϵ_{it} at time t, whereas the latter do not.

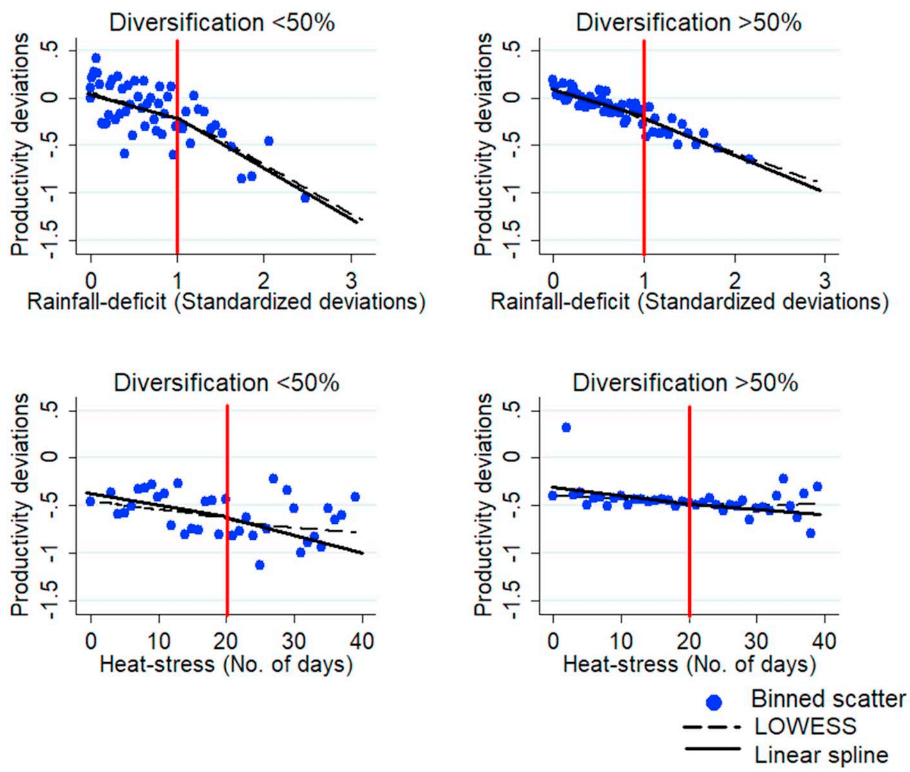

Fig. 5. Binned scatterplots of climatic shocks and productivity deviations.

the available evidence points towards a negative effect of heat-stress on crop yields. For wheat, Lobell et al. (2012) and Kaur and Behl (2010) show that an excessive rise in winter temperature at anthesis and graining filling stages adversely affects its yield. However, there are studies that show that winter crops may benefit from a rise in temperature, depending on the latitude at which these are grown, their growth stages and the management practices. Easterling et al. (2007), Ortiz et al. (2008), Gupta et al. (2010) and Jain et al. (2017) provide evidence that with the early sowing and use of stress-tolerant short-duration varieties and resource conservation practices it is possible to sustain yield gains even under heat-stress. Note that most studies on the relationship between heat-stress and crop yields have focussed on the

Table 5
GMM dynamic panel-data estimates.

	GMM estimation (Overall)	GMM estimation (Kharif)	GMM estimation (Rabi)
Ln Productivity $_{t-1}$	0.4279*** (0.0339)	0.1692***(0.0350)	0.37784***(0.0471)
Ln Productivity $_{t-2}$	0.2337*** (0.0171)	0.0588**(0.0249)	0.01867 (0.03572)
Ln Human labour	−0.2379*** (0.0882)	−1.0581***(0.2161)	0.00674 (0.1736)
Ln Human labour $_{t-1}$	0.2576*** (0.0870)	1.1001***(0.2187)	−0.02221 (0.1681)
Ln Fertilizer	0.0996*** (0.0140)	–	–
Ln Fertilize $_{t-1}$	−0.0567*** (0.0114)	–	–
Ln Tractor	−0.0458*** (0.0128)	−0.1292***(0.0372)	−0.07731 (0.0667)
Ln Tractor $_{t-1}$	0.0538*** (0.0147)	0.2115***(0.0385)	0.14181** (0.0661)
Ln Draught animal power	−0.0494 (0.0398)	0.2513*(0.1391)	−0.38317** (0.1579)
Ln Draught animal power $_{t-1}$	0.1399*** (0.0447)	−0.4094***(0.1457)	0.27377 (0.1693)
Irrigation	1.8839*** (0.20417)	−0.0593***(0.0109)	0.0185 (0.0277)
Irrigation $_{t-1}$	−1.3138*** (0.1930)	0.04422***(0.0085)	−0.12542** (0.0534)
Rainfall-deficit	−0.3122*** (0.0907)	−0.0695***(0.0338)	−0.01337 (0.03521)
Heat-stress	−0.3891 (1.7742)	−1.9436**(0.8876)	0.73439***(0.2611)
Diversification	1.1921*** (0.3124)	0.1707**(0.0918)	0.14154 (0.1411)
Diversification$_{t-1}$	−1.3195***(0.29384)	−0.1854**(0.0869)	0.14899 (0.0959)
Diversification x Rainfall-deficit	0.2884** (0.1420)	0.0325(0.0547)	0.05756 (0.0774)
Diversification x Heat-stress	−0.1926 (2.5849)	1.4522(1.4664)	−0.60285 (0.6092)
Diversification x Rainfall-deficit $_{t-1}$	0.0918*** (0.0293)	−0.1103***(0.0233)	0.00273 (0.0331)
Diversification x Heat-stress$_{t-1}$	1.9718*** (0.2956)	2.8187***(0.2550)	0.3433 (0.2809)
Constant	2.1149*** (0.3072)	5.6221***(0.3953)	5.01865*** (0.57303)
F test	561.63***	64.01***	26.97***
Arellano-Bond test (H$_0$: no first-order serial correlation)	7.83***	5.73***	7.04***
Arellano-Bond test (H$_0$: no second-order serial correlation)	0.89	1.52	0.48
No. of observations	13,124	11,709	10,925

Robust standard errors are in parentheses.
Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6
Short-run and long run marginal effects.

	Overall	Kharif	Rabi
Short-run			
Rainfall-deficit	−0.1274*** (0.0092)	−0.0505*** (0.0107)	0.0122 (0.0129)
Heat-stress	−0.5125*** (0.1869)	−1.0974*** (0.1501)	0.4655* (0.1059)
Diversification	1.4054*** (0.3066)	0.2099*** (0.0871)	0.1558(0.1558)
Long-run			
Rainfall-deficit	−0.3755 *** (0.0442)	−0.0901*** (0.0041)	−0.221*** (0.0016)
Heat-stress	−1.5112*** (0.1779)	−2.5181*** (0.1141)	1.2169*** (0.0903)
Diversification	4.1442*** (0.4879)	0.2211*** (0.0101)	0.2345*** (0.0174)

Figures in parentheses are standard errors.
Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$.

terminal heat-stress and not on the heat-stress at different crop growth stages. Notwithstanding, our findings clearly authenticate the role of diversification in enhancing resilience of agricultural production systems against climatic shocks.

Further, we have also estimated the marginal effects of diversification by severity of climatic shocks. In the short-run, the marginal effects of diversification under moderate and severe climatic shocks are estimated 1.727 and 2.190, respectively, and these are larger than the mean marginal effect of 1.404 (Fig. 6). In the long-run, the marginal effects improve considerably to 4.96 under moderate shocks and to 6.35 under severe shocks as against their mean of 4.14. These findings clearly reveal that adaptation benefits of diversification are larger against severe climatic shocks and in the long-run.

Earlier in this paper we had observed agricultural productivity varying across severity level of climatic shocks as well as degree of diversification. To investigate these relationships further, we undertake three counterfactual exercises. First, we estimate predicted relationship between agricultural productivity at different levels of diversification assuming no change in severity of climatic shocks. Results are presented in Table 7 and these confirm that adaptation benefits of diversification are quite robust.

Second, we simulate agricultural productivity at varying severity level of climatic shocks and degree of diversification with three counterfactuals: (i) the absence of diversification or complete specialization, (ii) the mean level of diversification, and (iii) the diversification exceeding 75% of its mean. Fig. 7A shows productivity response to the variation in rainfall-deficit at different levels of diversification. The productivity curve is negative, irrespective of the level of diversification. However, at higher level of diversification the productivity curve lies above its counterfactuals (i) and (ii). Interestingly, the productivity curve in the absence of diversification is much steeper than the ones representing the less-specialized production systems. This indicates that the negative impact of rainfall shocks is larger at lower level of diversification. Similarly for heat-stress, the productivity curve at a higher level of diversification is on a higher plateau, that suggests that diversification leads to an increase in agricultural productivity even under heat-stress (Fig. 7B). These findings confirm that crop diversification improves resilience of agriculture against climatic shocks.

Finally, we simulate agricultural productivity trends at different levels of climatic shocks using results from Eq. (3). There is a rising trend in agricultural productivity irrespective of the severity of rainfall shocks (Fig. 8A). But, the productivity curves under moderate and severe shocks lie below the curve with the low rainfall-deficit. Similarly, the productivity trends are positive despite the heat-stress, but the difference therein across severity of heat-stress is not as large as in the case of rainfall shocks (Fig. 8B). These findings suggest that farmers, besides crop diversification, also use other adaptation measures to cope with climatic shocks; for example, irrigation, stress-tolerant varieties and agronomic practices (Birthal et al., 2015).

5. Concluding remarks

Increasing frequency of extreme climatic events is threatening the sustainable development of agriculture and agriculture-based

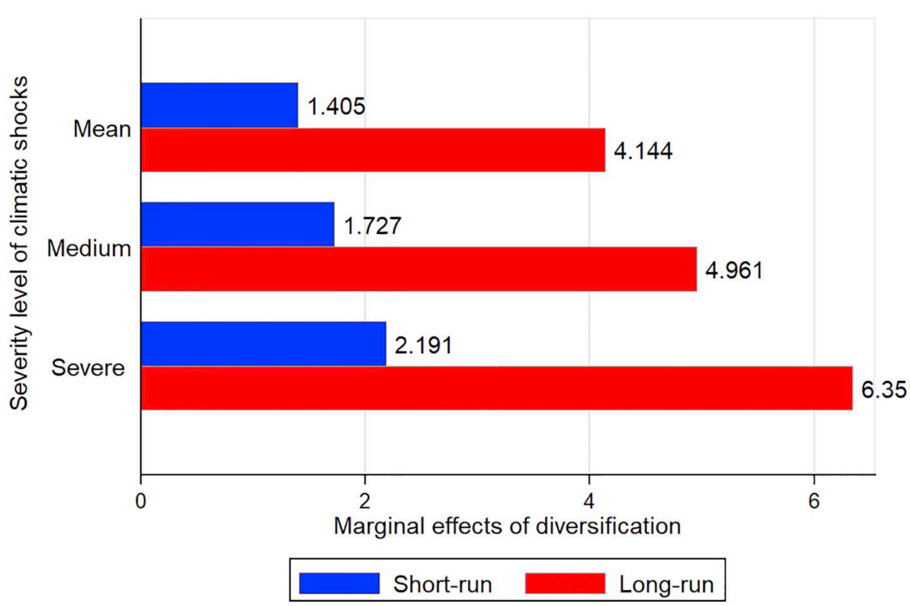

Fig. 6. Marginal effects of diversification by level of severity of climatic shocks.

Table 7
Predicted agricultural productivity at different levels of diversification.

	Level of diversification (%)							
	10	20	30	40	50	60	70	80
Log-Productivity	8.563 (0.17)	8.704 (0.14)	8.844 (0.11)	8.985 (0.08)	9.125 (0.05)	9.266 (0.02)	9.406 (0.02)	9.547 (0.05)

Figures in parentheses are standard errors.

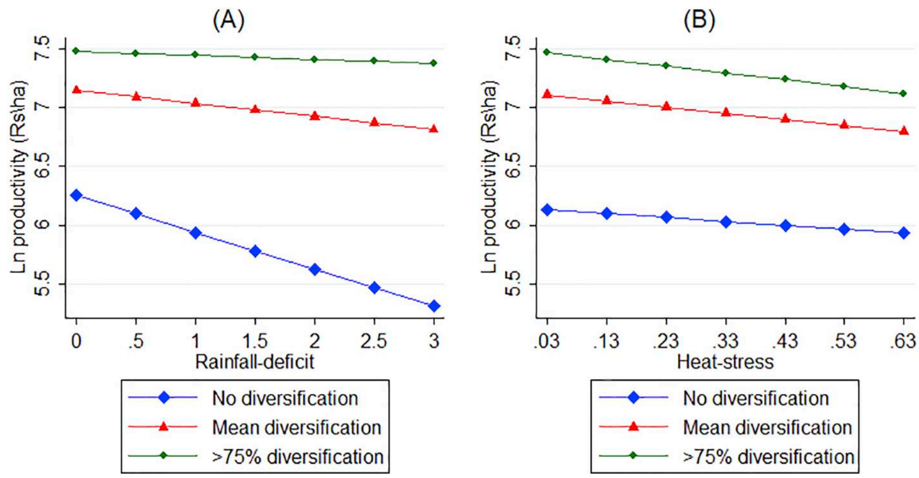

Fig. 7. Agricultural productivity under climatic shocks at different levels of diversification.

livelihoods, especially in developing countries, like India, because of their greater dependence on agriculture, small landholdings, and lack of financial resources, technologies, infrastructure and institutions to cope with such shocks, *ex ante* or *ex post*. In this paper, we have assessed effectiveness of crop diversification in mitigating harmful effects of climatic shocks, i.e., rainfall deficit and heat-stress, on agricultural productivity in a dynamic setting using district-level panel data.

Our findings show that agricultural productivity is adversely affected by climatic shocks and their effects become more pronounced with their rising severity. Nevertheless, we find crop diversification as one of the important *ex ante* adaptation measures in enhancing resilience of agriculture against such shocks. The adaptation benefits of diversification are dynamic and more apparent in the long-run.

These findings have two clear implications for policies aiming at making agriculture climate-resilient. One, the climatic shocks are location-specific; hence there is a need to strengthen location-specific early warning systems to provide farmers timely information on weather conditions so that they are better-prepared to choose crops and other agronomic practices in anticipation of a shock. Yet, another related issue is of strengthening the agricultural information and input delivery systems, especially for seeds and agronomic practices that play an important role in management of risks *ex ante*. Two, there is a need to emphasize research on crop breeding for stress-tolerance. Unlike other management options, stress-tolerant seeds are not expensive, are easy to multiply and provide long-term solution.

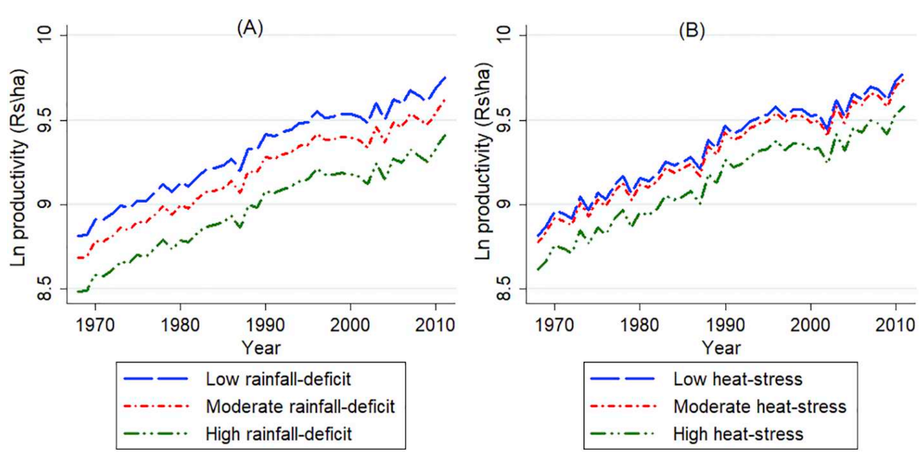

Fig. 8. Trends in agricultural productivity at different severity levels of climatic shocks

Acknowledgments

This work has been funded by the Indian Council of Agricultural Research under the National Professorial Chair to the first author.

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