

# Asymmetric impact of rainfall on India's food grain production: evidence from quantile autoregressive distributed lag model

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**Abstract** This study used a quantile autoregressive distributed lag (QARDL) model to capture asymmetric impact of rainfall on food production in India. It was found that the coefficient corresponding to the rainfall in the QARDL increased till the 75th quantile and started decreasing thereafter, though it remained in the positive territory. Another interesting finding is that at the 90th quantile and above the coefficients of rainfall though remained positive was not statistically significant and therefore, the benefit of high rainfall on crop production was not conclusive. However, the impact of other determinants, such as fertilizer and pesticide consumption, is quite uniform over the whole range of the distribution of food grain production.

## 1 Introduction

India is currently passing through a crucial time, when over a decade, India's food grain production has remained stagnant, or increased marginally, while population is registering a steady growth of 2 % annually. This has put the issue of food security at the centre of the discussion for every policy maker. What makes the issue so alarming is that Indian agriculture is till date predominantly rain fed with only 47.8 % of the cultivated land is covered under assured irrigation (Government of India 2013). India tops the list among the nations that follow

rain-fed farming in terms of coverage as well as output (Sharma et al. 2010). The rain-fed food production is under tremendous pressure due to shift in rainfall pattern, wide variation on hydrological setting as well as overdependence on ground water (Khan and Hanjra 2009). Rainfall pattern in India, more precisely the southwest monsoon that provides nearly 74 % of India's annual rainfall, has become highly inconsistent and prediction has become much challenging due to more of climatic variability (Deka et al. 2013; Goyal 2014; Mandal et al. 2015; Chattopadhyay and Chattopadhyay 2016). Additionally, India also faces rising demand for water from industrial and domestic sources thus reducing the availability of water for agriculture. Finally, overextraction of ground water has depleted the ground water aquifer (Gandhi and Namboodiri 2009) and that to the yearly depletion of  $54 \pm 9 \text{ km}^3$  between early 2002 and mid 2008 (Tiwari et al. 2009). Lack of assured water supply as well as delayed rainfall is believed to be contributing mostly to low crop yield (Panigrahi and Panda 2002). This makes annual precipitation most crucial for good harvest in India.

Several attempts have been made to assess the extent to which India's food grain production is affected by the variation in rainfall. As for example, Sarma and Gandhi (1990) estimated a production function for food grain in India employing rainfall, area under irrigation, fertilizer use and the area under high-yielding varieties (HYV) as explanatory variables. Singh (1993) investigated possible association between production variability of food grain with adoption of new technology. Working on a dataset from 1966 to 1967 to 1998 to 1999, Gandhi et al. (2004) used a Cobb–Douglas production function for wheat with the rainfall index, percentage of irrigated area, fertilizer use and the percentage of the area under HYV as input. Gadgil and Gadgil (2006) assessed the impact of summer monsoon on India's food grain production during 1951 to 2003. In these studies, rainfall has evolved

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as the most significant variable affecting India's food grain production. They found that owing to near stagnant growth of irrigation coverage, India's food grain production largely depends on rainfall. As all these scholarly contributions precisely relied upon the linear effect of the rainfall and other exogenous variables on the food grain production, ordinary least squares (OLS) method was commonly used. However, a low rainfall, without adequate irrigation facility, would obviously affect crop production, but a heavy precipitation with every possibility could also adversely affect total output by creating water logging in the field or even flood-like situations. Hence, rainfall is expected to carry a nonlinear impact on food grain production. Any presence of such asymmetric responses may question the efficacy of linear modelling been used so far in assessing food grain production with time series data.

We attempt to fill this gap by using the quantile autoregressive distributed lag model (QARDL), to examine whether rainfall carries asymmetric impact on food grain production. The QARDL model, proposed by Cho et al. (2015), that estimates conditional quantile function over time is capable of delivering significant insights on the nonlinear dynamics in time series modelling by controlling lagged explanatory variables and exogenous covariates.

We assume that rainfall, the proportion of land under HYV, fertilizer consumption and pesticide use would be the major contributing factors towards food grain production. The additional variable proposed here, i.e. pesticide use, is related to plant health and likely to carry a positive impact on production by minimizing pest and disease infestation. As this study did not find a significant effect of the proportion of land under HYV on food grain production, we include the rest three explanatory variables in the food grain production function for India. This is consistent with the analysis of Rao et al. (1988), which have shown that the introduction of HYV from 1966 to 1967 does not have a significant effect on total food grain production as HYV only boosted the yield of wheat crop while yield of several other food crops either remained unchanged or even declined.

This work contributes primarily in two ways. First, it captures an asymmetric impact of rainfall on India's food grain production, contravening the earlier efforts that assumed a linear effect of rainfall on food grain production. Second, here, we apply QARDL model, which has not yet been explored in the context of climatology and more specifically to capturing the nonlinear effect of precipitation on crop production.

The remaining of the paper is arranged as follows: in section 2, we outlay an overview of spread of rainfall in India. In section 3, we describe data. The econometric model is presented in section 4. Section 5 discusses the results. Section 6 concludes.

## 2 Spread of rainfall in India

India experiences uneven distribution across the country. The availability of assured rainfall is limited to only 8 % of the geographical area with another 20 % under high precipitation range. The balance 72 % of the geographical area receives medium to low rainfall (Table 1). Besides, annual rainfall is concentrated in a particular short period of the year. Table 2 shows data on season-wise distribution of annual rainfall and highlights that around three fourths of the annual rainfall is received within 4 months, i.e. June to September. Finally, due to varying hydrogeological settings across the country, there lies a wide variation in ground water recharge capacity.

Further, there lies wide disparity in irrigation coverage across food crops, while during 2010–2011, 92.1 % of the cultivated area under wheat crop had assured irrigation facility and for the rice crop only 58.6 % of the cultivated area was covered under irrigation (Government of India 2013). On the contrary, irrigation coverage regarding coarse cereals was much less and pegged at only 14.4 % during the corresponding period. This uneven reach of irrigation facility resulted in increased production risk for rain-fed coarse cereals (Singh 1993).

## 3 Data

To carry out the empirical investigation, we used annual time series data from 1971 to 1972 to 2011 to 2012. Table 3 describes data and lists the sources.

Table 4 outlays the summary statistics for the underlying variables. During the study period, India's total food grain production varied between 813.04 and 2059.01 million tonnes with an average of 1357.71 million tonnes and standard deviation of 364.04 t. Annual rainfall ranged between 697.40 and 1094.10 mm with standard deviation of 89.41 mm that portrays a wide variation in annual rainfall over years. Use of fertilizer has increased from as minimal as 21.77 to 281.22 million tonnes. Pesticide consumption has experienced a threefold increase from 24.32 to 75.89 thousand tonnes. The

**Table 1** Geographical spread of annual rainfall in India

Rainfall classification	Amount of rainfall (millimetre)	% of total geographical area
Low/dry	Less than 750	30
Medium	750–1150	42
High	1150–2000	20
Very high/assured	Above 2000	8
Total		100

Source: Fertiliser Association of India (2013)

**Table 2** Season-wise distribution of annual rainfall in India

Rainfall	Duration	Share of annual rainfall (%)
Pre-monsoon	March–May	10.4
Southwest monsoon	June–September	73.7
Post-monsoon	October–December	13.3
Winter or northeast monsoon	January–February	2.6
Total	Annual	100.0

Source: Fertiliser Association of India (2013)

third moment indicates that the distributions are positively skewed except for annual rainfall which is negatively skewed. The fourth moment shows that the distributions are leptokurtic, i.e. distributed with positive excess kurtosis or fatter tails.

### 3.1 Econometric specification

The proposed multivariate model is given below:

$$Y = f(R, F, P) \quad (1)$$

where  $Y$  is the major food grain production (in million tonnes),  $R$  is the annual rainfall (in millimetre),  $F$  stands for consumption of fertilizer (in million tonnes) and  $P$  represents the consumption of pesticide (in thousand tonnes).

First, we test the order of integration among the variables used in this study by employing augmented Dickey–Fuller test (Dickey and Fuller 1979) and Phillips–Perron test (Phillips and Perron 1988). We choose the number of lags according to Schwarz–Bayesian information criteria. We found that while annual rainfall was integrated of order zero i.e. stationary at levels, food grain production, fertilizer consumption and pesticide usage were stationary at their first differences.

As three of the underlying variables were nonstationary at levels, we checked whether the underlying variables were cointegrated. Cointegration is mainly applicable to nonstationary time series variables that would yield stationary residuals in the model. Following Xiao (2009), Lee and Zeng (2011) and Burdekin and Siklos (2012), the conventional

cointegration relationship between the model proposed in Eq. (1) is represented as follows:

$$Y_t = a_0 + b_1 R_t + b_2 F_t + b_3 P_t + \varepsilon_t \quad (2)$$

where  $t$  = time period = 1, 2, ...,  $n$  and  $\varepsilon_t$  is the random error.

We performed Trace test and Maximum Eigenvalue test advanced by Johansen (1991) as also employed in Lee and Zeng (2011) prior to using quantile cointegration regression proposed by Xiao (2009). Both the tests indicated that the underlying variables were cointegrated, i.e. there holds long-run association among the underlying variables.

Further, the long-run cointegrating target production relationship can be expressed into a form following an (unrestricted) autoregressive distributed lag (ARDL) model suggested by Pesaran et al. (2001) and Cho et al. (2015),

$$\begin{aligned} \Delta Y_t = & \alpha_0 + \beta_1 Y_{t-1} + \beta_2 R_{t-1} + \beta_3 F_{t-1} + \beta_4 P_{t-1} \\ & + \sum_{i=1}^{n1} \gamma_{1i} \Delta Y_{t-i} + \sum_{i=0}^{n2} \gamma_{2i} \Delta R_{t-i} + \sum_{i=0}^{n3} \gamma_{3i} \Delta F_{t-i} \\ & + \sum_{i=0}^{n4} \gamma_{4i} \Delta P_{t-i} + \varepsilon_t \end{aligned} \quad (3)$$

where  $\Delta$  is the first difference operator,  $\alpha_0$  is the drift component and  $n1$ ,  $n2$  and  $n3$  are lag orders and  $\varepsilon_t$  is the error.

The advantages of ARDL are as follows: first, ARDL can be made use irrespective of whether the variables are stationary at levels, stationary at their first difference or fractionally integrated. Second, it is possible to simultaneously estimate both long- and short-run parameters. Finally, ARDL can be

**Table 3** Data and sources

Variable	Description	Source
$Y$	Major food grain production (in million tonnes)	Ministry of Agriculture, Government of India, Database on Indian Economy - Reserve Bank of India
$R$	Annual rainfall (in millimetre) from June to September	Data Portal India, data.gov.in/
$F$	Consumption of fertilizer (nitrogen + phosphorous + potash) (in million tonnes)	Pattern of land use and select inputs for agricultural production. <i>Agricultural Statistics at a Glance</i> , Ministry of Agriculture, Government of India
$P$	Consumption of pesticides (technical grade materials) (thousand tonnes)	Chand and Birthal (1997) Database on Indian Economy - Reserve Bank of India

**Table 4** Summary statistics

Variable	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis
$Y$	1357.71	2059.01	813.04	364.04	0.02	1.75
$R$	879.99	1094.10	697.40	89.41	-0.17	2.77
$F$	122.89	281.22	21.77	74.96	0.44	2.27
$P$	48.99	75.89	24.32	12.50	0.60	2.73

used even when the independent variables are endogenous (Pesaran et al. 2001).

We also conducted  $F$  test of bounds testing approach proposed by Pesaran et al. (2001) to probe the existence of cointegrating relationship among the underlying variables at level values. The null hypothesis of no cointegration among the underlying variables in Eq. (3) is  $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$  against  $H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$  which is denoted as  $F_Y(Y|R, F, P)$ .

The test statistic of Pesaran and Shin (1998) and Pesaran et al. (2001) provided two separate sets of critical  $F$  statistic for  $I(0)$  and  $I(1)$  applicable on large samples. Another two sets of  $F$  statistic was developed by Narayan (2005) for comparatively smaller samples ranging from 30 to 80. As this study covers annual time series data spanning from 1971 to 1972 to 2011 to 2012, we followed Narayan (2005) for referring to  $F$  statistic. If the test statistic exceeds the upper bounds critical value, null of no cointegration is not accepted, and it can be established that a long-run relationship exists. If the calculated  $F$  statistic falls below the bounds critical value, then the null of no cointegration is not rejected. If calculated  $F$  statistic falls within the upper and lower bounds critical value, inference would be inconclusive. Here, the test statistic of  $F$  test had a value of 6.7586 that exceeded the upper bound value (i.e. 5.455 at 1 % level) suggested by Narayan (2005). Hence, the null of no cointegration was rejected and the presence of cointegration among the underlying variables was further confirmed.

In general, quantile regression (QR) proposed by Koenker and Bassett (1978) models conditional quantiles as functions of the explanatory variables. While OLS captures the change in the conditional mean of the regressand associated with a change in explanatory variables, the QR models variations over the conditional quantile. QR is preferred when there is asymmetry.

Cho et al. (2015) extended the idea of quantile cointegration proposed by Koenker and Xiao (2006) to develop a dynamic QARDL modelling approach which can simultaneously capture both long-run relationship and the associated short-run dynamics across a range of quantiles of the conditional distribution of the regressand in a fully parametric setting.

Following Cho et al. (2015), the quantile counterpart of the Eq. (3) i.e. the QARDL model at  $\tau^{\text{th}}$  quantile is as follows:

$$\begin{aligned} \Delta Y_t = & \alpha_0(\tau) + \beta_1(\tau)Y_{t-1} + \beta_2(\tau)R_{t-1} + \beta_3(\tau)F_{t-1} \\ & + \beta_4(\tau)P_{t-1} + \sum_{i=1}^{n1} \gamma_{1i}(\tau)\Delta Y_{t-i} + \sum_{i=0}^{n2} \gamma_{2i}(\tau)\Delta R_{t-i} \\ & + \sum_{i=0}^{n3} \gamma_{3i}(\tau)\Delta F_{t-i} + \sum_{i=0}^{n4} \gamma_{4i}(\tau)\Delta P_{t-i} + \varepsilon_{1t}(\tau) \end{aligned} \quad (4)$$

where  $\tau \in (0,1)$  is a quantile index and  $n1$ ,  $n2$  and  $n3$  are lag orders.

The conditional long-run model for  $Y_t$  can be attained by employing ARDL approach and the reduced form solution of Eq. (4) following the QARDL version of Cho et al. (2015) is as follows:

$$Y_t = \lambda_1(\tau) + \lambda_2(\tau)R_t + \lambda_3(\tau)F_t + \lambda_4(\tau)P_t + \nu_t(\tau) \quad (5)$$

where  $\lambda_2(\tau) = -\beta_2(\tau)/\beta_1(\tau)$ ,  $\lambda_3(\tau) = -\beta_3(\tau)/\beta_1(\tau)$ ,  $\lambda_4(\tau) = -\beta_4(\tau)/\beta_1(\tau)$  and  $\nu_t(\tau)$  is the random error.

## 4 Results and discussion

Setting  $\tau = 0.05, 0.10, 0.15, 0.20, \dots, 0.90, 0.95$ , we estimated Eq. (5) using QARDL method. For the purpose of comparison, Eq. (5) was also estimated using the OLS method. The estimation results are given in Table 5. These results are complemented by the figures of the coefficients for each variable in Eq. (5). For each of the three covariates, we plot 19 different QARDL estimates for  $\tau$  ranging between 0.05 and 0.95 as the solid curve. These point estimates show the impact of one-unit change of the covariate across various quantile on the food grain production keeping other covariates constant. Thus, each of the plots in Fig. 1a–c has a horizontal quantile, or  $\tau$ , scale, and the vertical scale in million tonnes indicating the impact of the covariates. The dotted line in each plot indicates the OLS estimate of the conditional mean impact. The shaded area plots a confidence band of  $\pm 1$  standard error ( $s$ ) for the QARDL long-run coefficients.

To assess whether the effect of drought as well as flood carries forward to the next period, we initially included lags

**Table 5** Estimated QARDL models for different quantiles of food grain production

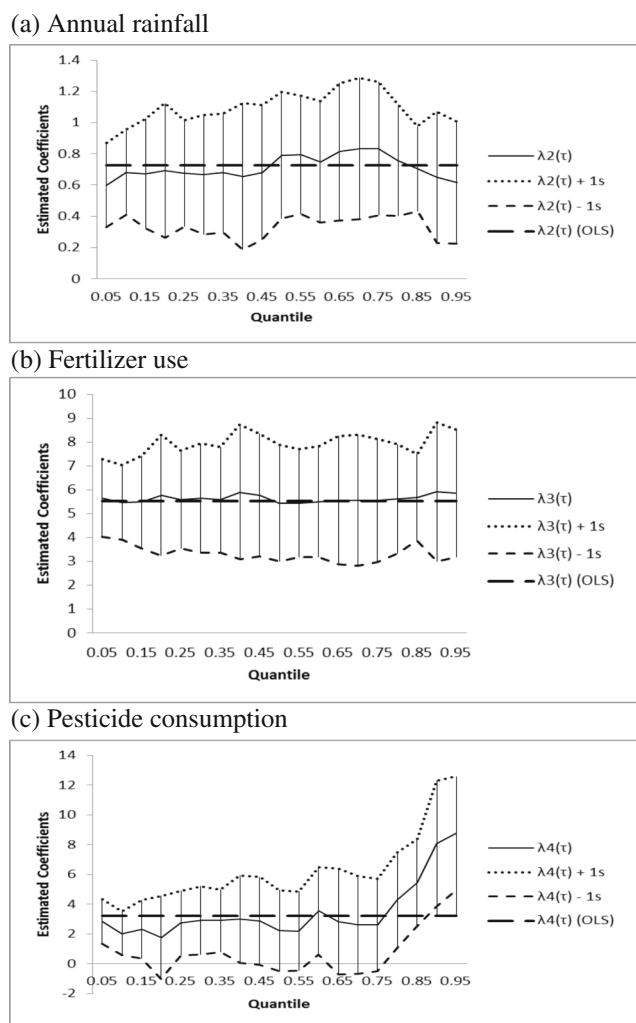
$\tau$	$\beta_2(\tau)$	$\beta_3(\tau)$	$\beta_4(\tau)$	$R^2/\text{pseudo } R^2$	$\lambda_2(\tau)$	$\lambda_3(\tau)$	$\lambda_4(\tau)$
OLS	0.453*** (-0.146)	3.448*** (-0.871)	1.998* (-1.014)	0.4268	0.725*** (0.2348)	5.516*** (1.3949)	3.197* (1.6231)
0.05	0.595** (0.2674)	5.616*** (1.6084)	2.824 (1.4992)	0.4925	0.599** (0.2694)	5.656*** (1.6199)	2.8447 (1.5099)
0.1	0.680** (0.2708)	5.467*** (1.5681)	2.031 (1.461)	0.3849	0.682** (0.2714)	5.478*** (1.5713)	2.0359 (1.4639)
0.15	0.550* (0.2876)	4.488*** (1.5917)	1.908 (1.6009)	0.3270	0.672* (0.3514)	5.484*** (1.9448)	2.3315 (1.956)
0.2	0.406 (0.2522)	3.379** (1.4886)	1.036 (1.6335)	0.3087	0.6937 (0.4309)	5.773** (2.5431)	1.7712 (2.7906)
0.25	0.526** (0.2655)	4.357** (1.6)	2.136 (1.6834)	0.3196	0.676** (0.3408)	5.591** (2.0533)	2.7418 (2.1604)
0.3	0.473* (0.2729)	4.026** (1.6273)	2.069 (1.6329)	0.3016	0.666* (0.3836)	5.659** (2.2872)	2.9084 (2.2951)
0.35	0.509* (0.2854)	4.194** (1.6586)	2.178 (1.5781)	0.2813	0.678* (0.3799)	5.583** (2.2077)	2.8995 (2.1006)
0.4	0.358 (0.2575)	3.231** (1.5439)	1.637 (1.6132)	0.2589	0.655 (0.4703)	5.901** (2.82)	2.9905 (2.9466)
0.45	0.404 (0.2559)	3.431** (1.5296)	1.702 (1.7548)	0.2397	0.681 (0.4308)	5.777** (2.5751)	2.8661 (2.9542)
0.5	0.510* (0.2606)	3.502** (1.5732)	1.427 (1.7542)	0.2304	0.792* (0.4045)	5.436** (2.4418)	2.2161 (2.7227)
0.55	0.511** (0.2427)	3.501** (1.458)	1.422 (1.7123)	0.2272	0.7938** (0.3766)	5.4344** (2.2627)	2.2079 (2.6574)
0.6	0.449* (0.2333)	3.309** (1.3976)	2.127 (1.7685)	0.2506	0.748* (0.3885)	5.510** (2.327)	3.5415 (2.9445)
0.65	0.4225 (0.2282)	2.887** (1.3941)	1.468 (1.8415)	0.2846	0.8141 (0.4397)	5.563** (2.6863)	2.8297 (3.5485)
0.7	0.421* (0.2313)	2.836** (1.3975)	1.329 (1.6791)	0.3046	0.831* (0.4535)	5.559** (2.7398)	2.606 (3.2919)
0.75	0.425* (0.2178)	2.836** (1.3148)	1.329 (1.5777)	0.3137	0.834* (0.4269)	5.559** (2.5777)	2.606 (3.0929)
0.8	0.409** (0.1929)	3.040** (1.2366)	2.309 (1.7203)	0.3182	0.757** (0.3568)	5.624** (2.2874)	4.2716 (3.1821)
0.85	0.390** (0.1503)	3.150*** (1.0049)	3.019* (1.6233)	0.3125	0.705** (0.2714)	5.691*** (1.8152)	5.454* (2.9321)
0.9	0.259 (0.1676)	2.352** (1.1557)	3.221* (1.677)	0.3559	0.650 (0.421)	5.907** (2.9027)	8.091* (4.2119)
0.95	0.250 (0.1587)	2.376** (1.0841)	3.565** (1.5428)	0.4253	0.616 (0.3907)	5.850** (2.6689)	8.778** (3.7981)

Standard errors are shown in parentheses

\*\*\*Significant at a level of 1 %, \*\*significant at a level of 5 %, \*significant at a level of 10

in our model. We started with two lags to be sure that whether the effect of drought or flood carries forward for two successive years. To reach a parsimonious model, we followed a general-to-specific modelling method by sequentially dropping variables with high  $p$  values, i.e. those do not carry

statistically significant effect on food grain production. As both the lags were attached with high  $p$  values they were not included in the model. Hence, we attain zero lag of rainfall in our final model. The choice of lag was also confirmed by Schwarz–Bayesian information criteria. This seems plausible



**Fig. 1** a–c OLS and QARDL estimates for the long-run coefficients of food grain production model

as given wide geographical spread of Indian territory the effect of scanty as well as bounty precipitation is felt regionally, unless the shortfall or excess rainfall is experienced across the country. As during our study period, drought or flood has been experienced regionally; their effect is marginal on India's total food grain production. Hence, the effect of annual precipitation—whether shortfall or excess—remained confined to the particular year.

According to the OLS estimation, annual rainfall was positively affecting the food grain production and statistically significant at the convention levels. The QARDL results, while supplementing the OLS outcome, painted a different picture. The higher the quantiles were, the greater the estimated values of  $\lambda_2(\tau)$  and reached to its peak (i.e. 0.834) at  $\tau = 0.75$  and further reduced and came down to 0.616 at  $\tau = 0.95$ , which was closer to the estimated values of  $\lambda_2(\tau)$  at  $\tau = 0.05$  (i.e. 0.599). The decreasing trend of  $\lambda_2(\tau)$  values above 75th quantile indicated that excess rainfall is detrimental to crop production, while this feature could not be captured

in OLS. The inverted 'U' shape of the coefficient associated with the rainfall parameter (refer Fig. 1a) was expected as food grain production was adversely affected by both scanty rainfall and drought and incremental benefit of rainfall reduces in case of excessive rainfall, i.e. above the 75th quantile. The coefficients corresponding to rainfall though remained positive was not statistically significant at 90th and 95th quantiles.

Fertilizer use was associated with a modest increase in food grain production. It had a reasonably uniform impact over the entire range of the distribution of around 5.5 million tonnes (b). The behaviour was consistent with the earlier research (see for example, Sharma and Thaker, 2010) which indicated that heavy subsidization of nitrogenous fertilizer (e.g. urea) while in one hand had led to imbalanced use of nitrogen, phosphorous and potash and hence negatively affected soil fertility and productivity, on the other hand, had also resulted in uneven use of fertilizer across crops. Therefore, a uniform effect of fertilizer on food grain production seems to be plausible.

Coefficient associated with the pesticide use was found to be positive and significant at the level of 10 % under the OLS. This indicates that pesticide use carries positive impact on food grain production though not highly significant. This seems plausible as right use of pesticide prevents crop loss from pest and disease attack. The results of the QARDL portray a different picture to that of the OLS (c). The results of OLS show a uniform boosting effect of pesticide use on the food grain production. However, under QARDL pesticide use was significant only at 85th quantile and above however significant only at the level of 10 %. In the lower quantiles though the coefficients were positive, they were not statistically significant. This indicates that the effect of pesticide use on food grain production varies with the extent of pesticide use. This means that the restricted use of pesticide has only limited effect in preventing crop loss.

## 5 Conclusion and policy implication

This study confirms asymmetric impact of rainfall on India's food grain production. This result is important for India as food grain production in India is heavily dependent on rainfall and only 47.8 % of the cultivated area is covered under irrigation. The irrigation facilities developed so far have been largely sustained on ground water resources. Groundwater irrigates (27 million hectares) a larger total area than surface water (21 million hectares). However, water table is declining almost all over the country due to heavy dependence on ground water irrigation. This has become a serious concern for policy makers in terms of retaining self-sufficiency in food grain against an annual population growth of 2 %. With irrigation being the 'leading input' (Ishikwa 1967) as precondition for other technological improvements to yield higher

production and given depleting water table due to overdependence on ground water, government puts more thrust on surface irrigation. A further addition of the surface irrigation facility, in the one hand, would reduce dependence on rainfall and on the other would ensure an outflow of stagnant water from the flooded regions.

The importance of rainfall in Indian agriculture also arises due to the uneven distribution of rainfall across the country. Availability of assured rainfall is limited to 8 % of the geographical area with another 20 % under high precipitation range. The balance 72 % of geographical area receives medium to low rainfall. These necessities developing water resources for assured water supply across the region as well as across seasons remain vital to achieve the desired growth in agricultural production. In India, where dearth of public investment in the development of surface water irrigation has forced the farmers to opt for private investment to extract ground water, the innovation of the semi-circular check dam is a boon. So, one can construct more dams at the same cost required to build a single straight line check dam (Gupta 2007). In low rainfall or drought prone areas, ten small dams with a catchment of 1 ha each are capable of collecting more water than a single dam with 10 ha of catchment area (Agarwal 2001). Low-cost precision irrigation systems may also be advocated for the judicious use of water as drip and sprinkler irrigation save water to the extent of 50 and 25 %, respectively (Dhawan 2001).

Furthermore, around three fourth of India's rainfall is concentrated within a 4-month period, i.e. June to September, that is credited to the southwest monsoon. Given limited check dam facility, a major part of the water either percolates to soil or drains to ocean. Building adequate number of check dams, reservoirs as well as water harvesting facilities are advocated to store rain water which can be used for food grain production during the deficit years. The storage tanks as well as reservoirs would harvest water during the rainy season to mitigate water requirement during the post-monsoon dry spells (Jain and Kumar 2012). Harvesting the excess rain water would arrest the devastating impacts of the dry spells on rain-fed agriculture.

Innovative crop practices such as intermittent submergence and transplanting of paddy seedlings during the onset of monsoon that saves 25–40 % of irrigation water (Dhawan 2001) should be promoted to reduce the dependence on rainfall.

Finally, participatory water resource management is the need of the hour where communities have to be encouraged to manage, maintain and finance their water supply systems. It is also necessary to build the capacity of water managers and local organizations, to help them use participatory approaches, carry out needs assessments and plan and design systems creatively in partnership with farmers for promoting judicious use of rain water.

In this work, we used the quantile ARDL method of Cho et al. (2015) to find the determinants of food grain production in India. QARDL modelling approach jointly captures both short-run dynamics and long-run cointegration across a range of quantiles of the conditional distribution of the response variable. Significant differences were observed between the quantiles and OLS estimates. We found an asymmetric effect of precipitation on food grain production. The impact of rainfall increased till 75th quantile and started decreasing thereafter, though it remained in the positive territory.

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