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Impact of economic growth and population on agrochemical use: evidence from post-liberalization India

Amarendra Pratap Singh · K. Narayanan

Abstract   This paper analyzes the impact of population and per capita income on agrochemical use in India. Traditionally, few researchers have used $I = PAT$ equation in its original form to study the impact of population and per capita income on agrochemical use. In this paper, a variant of $I = PAT$ is used which relates per capita income and per hectare population with per hectare agrochemical use. The sample covers the period 1990–2008 for 25 Indian states. Our results suggest that per capita income has a nonlinear relationship with per hectare agrochemical use. Observed negative relationship between pesticide use per hectare and persons per hectare is indicative of public awareness regarding harms related with intensive use of pesticides; however, a positive relationship between fertilizer consumption per hectare and population pressure, found here, reiterates importance of fertilizers for food security. An examination into dematerialization of agriculture is also carried out at all India level which indicates that declining intensity of fertilizer and pesticide use in post-1990 period is mainly attributed to structural change in the economy. In summary, the paper concludes that India needs environment friendly agriculture policies and rural infrastructure to manage agriculture-related environmental problems.

1 Introduction

Increasing food supply requires the intensification of agriculture, as land available for food production is limited. Intensifying agriculture involves use of improved crop varieties and

A. P. Singh (✉) · K. Narayanan
Department of Humanities and Social Sciences, IIT Bombay, Mumbai, India
e-mail: amarendra20383@gmail.com

K. Narayanan
e-mail: knn@hss.iitb.ac.in

the more intensive and/or more efficient use of water, fertilizers, and other plant nutrients. Intensive use of chemical fertilizers, which remain fundamental to growth in food production achieved during last half century, is now widely considered as counterproductive (Maston et al. 1997; Tilman et al. 2002; Jorgenson and Kuykendall 2008). Use of fertilizers and other plant nutrients goes hand in hand with the more intensive use of pesticides, in spite of the fact that pesticides themselves do not contribute to increase productivity, but only help to reduce losses caused by pests, plant pathogens, and weeds. Chemical use in agriculture forms a vicious cycle in which producers are forced to apply incremental amounts of chemical inputs each time to maintain productivity while compromising sustainability of agriculture resources (see Fig. 1). In addition, low utilization efficiency of agrochemicals, absent mechanisms for agricultural waste disposal, and increasing scale of agricultural operations further accentuate agriculture-related environmental problems (Maston et al. 1997; Tilman et al. 2002). Environmental issues associated with agricultural intensification essentially refer to a discrepancy between increasing demand for food and the limited carrying capacity of agroenvironmental resources which in turn implies a divergence between growth in output and environment quality (Li et al. 2014).

Pesticide exposure events, soil nutrient imbalance due to inefficient fertilizer use, and agrochemical-driven water pollution are growing concerns for policy makers in India (Ghosh 2004; Rao and Puttana 2006). India is thus being confronted with the challenges of growing negative effect of agrochemical use while meeting its increasing food requirements to feed growing population. Against this background, this paper examines the impact of economic development on agrochemical use in post-liberalization India (1990
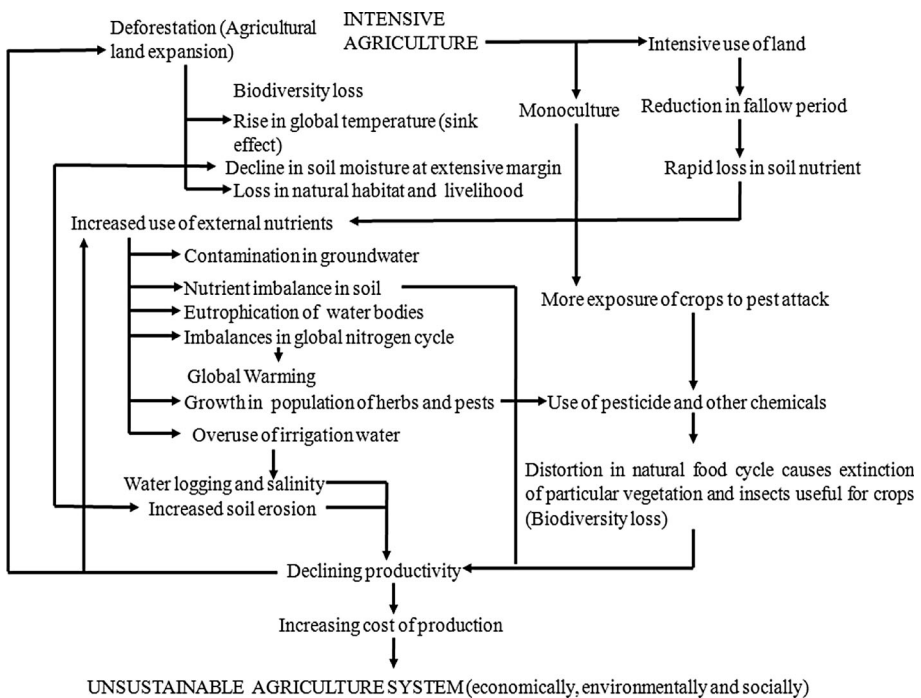

Fig. 1 Flowchart showing impact of intensive agriculture on agricultural sustainability (Singh and Narayanan 2012)

onwards). To our knowledge, this is the first attempt by any researcher to analyze the impact of economic development on agrochemical use in India.

2 Background

It is an old held view that increasing population and economic growth-driven urbanization exerts considerable impact on the agricultural resources (Boserup 1976; Meadows et al. 2004). Economic and demographic expansion primarily exhibits a scale effect that accelerates agricultural intensification which eventually has a negative impact on agro-environmental resources in the early development stages of an economy when average affluence level of society remains low (Dinda 2004; Brock and Taylor 2005). Nutritional transition (food grains to nonfood grains) which occurs at relatively higher levels of per capita income also exerts adverse impact on agroenvironmental resources through intensification (Tilman et al. 2002; Pretty 2008; Cole and McCoskey 2013). It is believed that intensive use of agrochemicals in developing countries is increasing rapidly because these countries prefer food security over food safety and environmental quality (Ecobi-chon 2001; Wilson and Otsuki 2004; Schreinemachers and Tipraqusa 2012). However, the view that economic growth is always damaging to environment quality seems to be true only in a static world where an economy is constrained to a fixed production possibility curve (Grossman and Kruger 1995; Antle and Heidebrink 1995; Schreinemachers and Tipraqusa 2012). A convergence in economic growth and agriculture-related environ-mental quality can be achieved via composition, technology, and abatement effects which come into play at higher levels of economic development. Population also plays a positive role in moderating agrochemical use as densely populated countries show a strong ten-dency to mitigate pollution side effects irrespective of the income levels (Panayotou 1997).

Composition effect comes into play where there is an increase in cleaner production practices that release pressure from the environment. Certain environmental attributes of agriculture can be transformed into a marketed output which may, in turn, encourage farmers for protecting agricultural environment voluntarily (Lichtenberg 2002). Addi-tionally, market-based instruments can be used to motivate producers for reducing emis-sion from agriculture (Dinar et al. 2012). Similarly, at high levels of income, demand for hazard-free food and clean environment grows and demand constraints induce producers and governments to give more attention to environmental concerns (Ruttan 1971; Dasgupta et al. 2002; Dinda 2004). Composition effect may also reduce pressure from environment via the price effect. In the early stages of development, heavy exploitation of agricultural resources takes place to support industrialization. Intensive agriculture leads to resource degradation, and the flow of agroenvironmental services (soil fertility, recharging of aquifers) starts declining over time. Declining supply of environmental services essential for agricultural production will eventually develop a market for these resources, and prices begin to reflect true scarcity of resources. Changes in input mix due to increasing scarcity of certain inputs may help to reduce pollution arising due to agrochemical use (Schrei-nemachers and Tipraqusa 2012).

Li et al. (2014) argue that lack of economic resources restricts developing societies to use technological or regulatory means to abate agricultural pollution. Another kind of threshold effect can be explained in terms of institutional and policy barriers which restraint developing societies to regulate pollution. Appropriate institutional structure reduces uncertainty in exchange, reduces transaction and production cost, and improves

allocative efficiency (Culas 2007). Appointment of Institutions to ensure efficient use of agrochemicals bears huge fixed costs which an economy may not afford in early stages of development. In addition, government macroeconomic policies such as input subsidy have unintended adverse effects on the conservation and use of environmental resources.

A number of researchers have recently considered economic growth and demographic factors in order to explain sources of agrochemical use and/or agricultural pollution. In this line, Arahata (2003) finds a cubic relationship between per capita income and insecticides and fungicides; however, a quadratic relationship is observed for herbicides. Jorgenson (2007) concludes that less developed countries with high level of foreign capital inflow tend to use more pesticides per hectare. In another study, Jorgenson and Kuykendall (2008) find pesticide and fertilizer consumption to be positively related to the level of foreign investment in the primary sector. Longo and York (2008) use data from a cross-section of countries to show that fertilizer and pesticide consumption follows an inverted U relationship with per capita income. In addition, this study also confirms the view that increasing trade is positively related to fertilizer and pesticide consumption. Ghimire and Woodward (2013) in a cross-country panel study reveal that countries at lower per capita incomes tend to under use pesticides while countries at vary higher end may be over using them. Li et al. (2014) examine EKC hypothesis for four types of agroenvironmental indicators, for a panel data set comprising 31 Chinese provinces. This study confirms an inverted U relationship between agroenvironmental indicators and per capita GDP.

Economic growth in India during post-liberalization period has widened the gap between agriculture and other economic sectors. While other sectors showed rapid economic growth in post-liberalization period, agricultural growth decelerated. A natural outcome of deceleration in agriculture growth has been its increasing reliance on public investment which remained constrained in post-liberalization era due to fiscal restrictions on government spending. In addition, public investment in agriculture has also been inadequate due to huge fertilizer and irrigation subsidies provided by the government to ensure profitability of agriculture. It is required considering the fact that India follows an administered pricing policy which is essential to run a huge public distribution network. India still lacks infrastructure to handle rural environmental problems, and supply of environmental policies is not adequate. Therefore, most of the environmental problems related with agrochemical use in India can be considered as a by-product of inappropriate input use policies and lack of adequate agricultural infrastructure in rural areas.

3 Approach

Impact of human activities on agriculture and its related environment is a well-established issue in the scientific literature. However, it is more important to determine what specific factors affect intensification process and the relative contribution of these factors on measure of intensification. $I = PAT$ equation (Ehrlich and Holdren 1971; Commoner 1971, 1972) is widely used by the researchers as a tool to analyze determinants of environmental quality. $I = PAT$ equation postulates that interaction of affluence (A), population (P), and technology (T) determines environmental impact (I). Unlike Longo and York (2008) who use quantity of agrochemical as a measure of impact, we use quantity of agrochemical use per hectare as a measure of impact. To match dimensionality of impact and driver side (Chertow 2001; Waggoner and Ausubel 2002), we use back substitution to write:

$$\frac{Q}{L} = \frac{Q}{Y} \times \frac{Y}{P} \times \frac{P}{L} \tag{1}$$

where Q, L, Y, and P stands, respectively, for quantity of agrochemical used in agriculture, cultivated area, domestic output[1], and population. Defining agricultural commodities demanded by population for consumption (C) as net of domestic output and trade (T), we can write Eq. (1) as:

$$\frac{Q}{L} = \frac{Q}{Y} \times \left(\frac{C}{P} \pm \frac{T}{P} \right) \times \frac{P}{L} \tag{2}$$

For a densely populated country having large and diverse agricultural system, agricultural trade per capita $\left(\frac{T}{P} \right)$ is negligible relative to per capita production. Assuming $\left(\frac{T}{P} \right) \cong 0$ in Eq. (2) gives:

$$\frac{Q}{L} = \frac{Q}{Y} \times \frac{C}{P} \times \frac{P}{L} \tag{3}$$

Equation (4) implies that agrochemical use per unit of land $\left(\frac{Q}{L} \right)$, i.e., impact ($I$), is determined by the interaction of chemical use per unit of agricultural production $\left(\frac{Q}{Y} \right)$, i.e., intensity (or efficiency) of agrochemical use (T), per capita consumption of agricultural commodities $\left(\frac{C}{P} \right)$, i.e., affluence ($A$) and number of persons per unit of agricultural land $\left(\frac{P}{L} \right)$, i.e., population pressure on agricultural land (P).

Deitz and Rosa (1997) employ $I = PAT$ identity in a stochastic framework in which relative contribution of components can be empirically investigated using econometric methods. Stochastic version of $I = PAT$ (*STIRPAT*) for Eq. (3) can be given as

$$\left(\frac{Q}{P} \right)_{it} = \alpha_i \left(\frac{C}{P} \right)_{it}^{\beta} \left(\frac{P}{L} \right)_{it}^{\gamma} \varepsilon_{it} \tag{4}$$

where subscripts i and t are added to emphasize that variables vary over time and space. $\alpha, \beta, \gamma, \theta$ and ε are the parameters to be estimated. Technology (T) in Eq. (5) is modeled as a residual and captures institutional and organizational (social political and economic) changes in the economy along with technological change (Deitz and Rosa 1997). Stochastic variant Eq. (4) reduces to initial $I = PAT$ formulation when $\alpha = \beta = \gamma = 1$. Linear regression models in which all variables are measured in logarithmic form can be formulated for hypothesis testing using Eq. (5) which is a logarithmic transformation of Eq. (4).

$$\ln \left(\frac{Q}{P} \right)_{it} = \ln \alpha_i + \beta \ln \left(\frac{C}{P} \right)_{it} + \gamma \ln \left(\frac{P}{L} \right)_{it} + \ln \varepsilon_{it} \tag{5}$$

Per capita food consumption shows a nonlinear relationship with per capita income (W), since demand for agrochemicals and other agricultural inputs is derived from demand for agricultural commodities; therefore, nonlinearity can be assumed between agrochemical use and per capita income. In addition, discussion in earlier section suggests that increasing per capita income enables farmers to use agricultural inputs more intensively and dispose chemical residuals more effectively. Similarly, economic growth allows governments to

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[1] For simplicity, we assume a homogenous agricultural output, say 'Food'.

raise institutions and bring policies for effective waste disposal in later phases of development.[2] Incorporating assumed nonlinearity between agrochemical use and per capita income gives:

$$\ln \left(\frac{Q}{L}\right)_{it} = \ln \alpha_i + \theta_1 (\ln W)_{it} + \theta_2 (\ln W)_{it}^2 + \gamma \ln \left(\frac{P}{L}\right)_{it}^{\gamma} + \varepsilon_{it} \qquad (6)$$

where θ_1, θ_2 and γ are parameters to be estimated using a statistical technique.

To enhance our understanding regarding impact of population on agrochemical use, we introduce population growth as an additional explanatory variable. Population growth is regarded as an important determinant of agriculture intensification, especially when it is not possible to increase food production by introducing more land under agricultural operations. In addition, population growth may have an indirect impact on agrochemical use through its impact on demographic processes like urbanization, age structure, and household size (Liddle 2014). Additionally, most of the agrochemicals can be applied in diluted form only; therefore, availability of irrigation is a prerequisite for use. Considering this fact, we include share of irrigated agricultural land as a factor explaining use of agrochemicals. Based on the discussion in the section, estimation model takes the following form for each agrochemical:

$$\ln \text{PESTH}_{it} = \alpha_i + \beta_1 (\ln \text{NSDPPC})_{it} + \beta_2 (\ln \text{NSDPPC})_{it}^2 + \beta_3 (\ln \text{POP}/H)_{it} + \beta_4 (\ln \text{IRS})_{it} + \beta_5 (\text{PG})_{it} + \varepsilon_{it}$$

$$(7)$$

$$\ln \text{FERTH}_{it} = \alpha_i + \beta_1 (\ln \text{NSDPPC})_{it} + \beta_2 (\ln \text{NSDPPC})_{it}^2 + \beta_3 (\ln \text{POP}/H)_{it} + \beta_4 (\ln \text{IRS})_{it} + \beta_5 (\ln \text{PG})_{it} + \varepsilon_{it}$$

$$(8)$$

4 Analysis

4.1 Data and variable construction

The data for the analysis are extracted from various sources such as all India series of GDP, and agrochemical use is borrowed from Handbook of Statistics on Indian Economy [Reserve Bank of India (RBI)]. Net state domestic product (NSDP) and NSDP per capita (NSDPPC) are the series at constant 1999–2000 prices, drawn from Handbook of Statistics on Indian economy (RBI). State-wise pesticides use (in terms of active ingredients) data are borrowed from Indiastates.com. State-wise information on fertilizer consumption (in terms of nutrients) is obtained from Harvest Database [Centre for Monitoring Indian Economy (CMIE)]. Mid-year state population series is extracted from Indian Intelligence Database (CMIE). Due to the unavailability of pesticide data, the sample covers period from 1990 to 2008 only. As data for all years are not available for all 25 states, the panel is

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[2] Environmentally less harmful substitutes of agrochemicals are available in form of bio-pesticides and bio-fertilizers. Availability of close substitutes suggests that with increasing prosperity use of bio-pesticides and bio-fertilizers may increase. Additionally, we don't find any reason why use of chemical pesticides and fertilizers will increase after showing a declining trend as declining use of agrochemicals will partially be an outcome of increasing use of bio-fertilizers and bio-pesticides.

Table 1 Definition of variables

Sl. no.	Variable	Notation	Definition and unit	Transformation
01	Fertilizer consumption per hectare	FERTH	$(N + P + K)$ fertilizer consumption/net cultivated area (in Kg per hectare)	Logged
02	Pesticide consumption per hectare	PESTH	Pesticide consumption/net cultivated area (in Kg per hectare)	Logged
03	Net state domestic product per capita	NSDPPC	In constant 1999–2000 Indian National Rupees (INR)	Logged
05	Population pressure on agriculture	POP/H	Population/net cultivated area (in person per hectare)	Logged
06	Population growth	POPG	$[\ln P_{it} - \ln P_{i(t-1)}]$ where P_{it} is mid-year population in state i at time t	Logged
07	Irrigated land share	IRS	Net irrigated area/net cultivated area	Logged

unbalanced. While using fertilizer and pesticide consumption data is not very precise from the environment perspective, these are the best available proxies for agriculture intensification and agroenvironmental quality and have, therefore, been used by other researchers (see Longo and York 2008; Ghimire and Woodward 2013; Li et al. 2014). Detailed description related to variable construction and their transformation is provided in Table 1.

4.2 Development of intensity of agrochemical use (IU) and affluence (GDP per capita) in India

In the following section, we analyze the intensity of pesticide and fertilizer use using all India level data. IU is defined as the physical quantity of resource that is used to produce one unit of GDP (Ausubel and Waggoner 2008). Defined in this way, a declining IU plot indicates increasing efficiency of resource use. Increasing efficiency (declining IU) may be an outcome of structural shift in the economy. To observe the impact of structural shift on IU, change in IU is decomposed into change due to increasing/decreasing efficiency within sector and change due to structural shift in economic activities.

Declining IU plots (Fig. 1) indicates increasing efficiency of agrochemical use in Indian agriculture. During 19-year span, fertilizer IU declined to 0.64 and pesticide IU declined to 0.18. Relatively flatter slope of fertilizer IU plot highlights importance of fertilizers to agricultural productivity. In addition, a definite upward shift is visible in fertilizer IU during 1996. A sharp decline in pesticide IU is observed during the study period largely attributed to the awareness created by the Union Carbide tragedy which generated immense public outrage against pesticides in India. Democratic response to minimize/prohibit pesticide use aftermath the tragedy is reflected in various antipesticide legislations by state as well as central governments at regular intervals.[3] In addition, India has started focusing on integrated pest management (IPM) much earlier (mid-1990s) with a focus to educate farmers regarding better pest management (Fig. 2).

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[3] Laws and regulations to prohibit use of certain pesticides not only act to ban pesticide use but also create wide awareness against pesticides use.
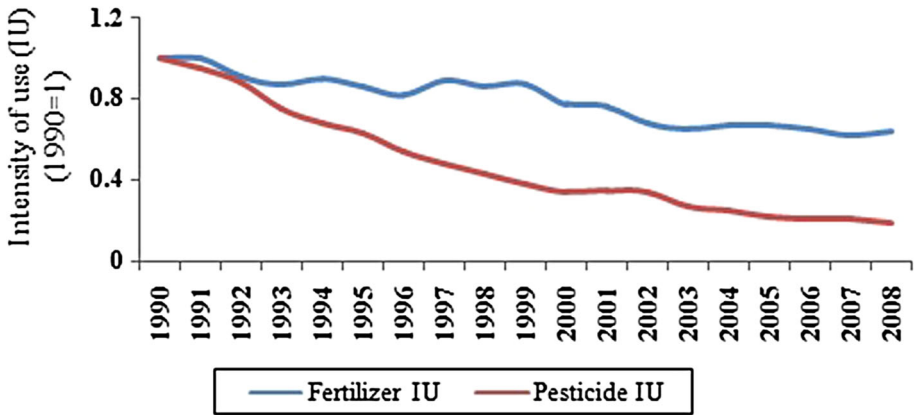
Fig. 2 Intensity of use (IU) plot for agrochemicals in India (1990–2007)
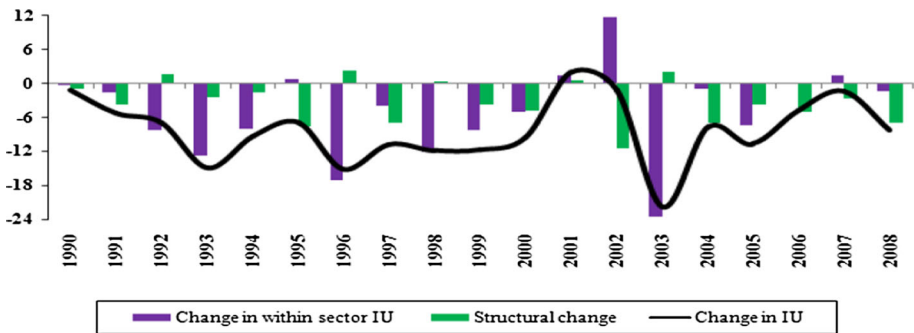

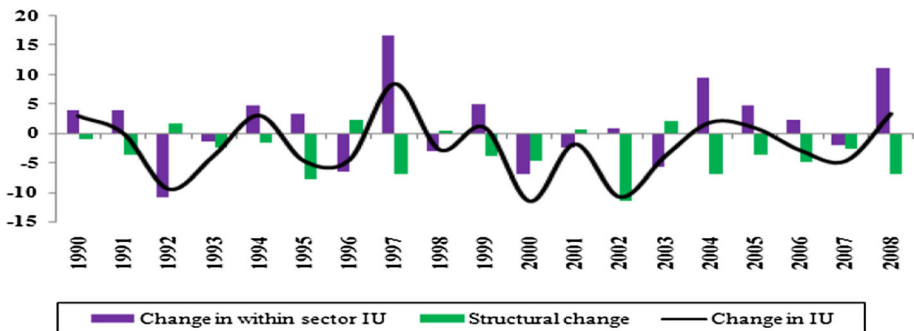Fig. 3 Decomposition of intensity of pesticide use

Fig. 4 Decomposition of intensity of fertilizer use

Decomposition results for fertilizer IU indicate that change in within sector fertilizer IU remains positive in most of the years but strong structural shift effect turns change in fertilizer IU negative (see Fig. 3). The case of pesticides is different from fertilizer, and a

continuous negative change in within sector IU along with structural shift effect leaves change in IU negative during most of the period (see Fig. 4). Results, here, indicate that a large share of declining intensity of agrochemical use in post-1990 period is explained by the rapid structural change in the economy; however, increasing pesticide efficiency also stands as an important factor behind sharp decline in pesticide IU.

4.3 Regression methodology and results

Considering heterogeneous diffusion of technology across Indian states, an analysis at disaggregated (state) level will substantiate observations made in previous section. In this section, we discuss the econometric method used to estimate the relationship between agrochemical use and its determinants and the resulting findings would be introduced thereafter.

Compiling state level data over years turns the data into a time series cross-section (TSCS) (or longitudinal/panel) data. Since we are interested in knowing the common trends among the units, data are pooled so that one regression equation represents all the units (states). A matter of great concern in econometric studies is the danger of spurious regression when the data are nonstationary. Most variables used in the macroeconomic environmental analyses are stock variables (population, GDP, etc.). These variables are typically trending and quite possibly nonstationary. Therefore, before employing other techniques, unit root properties of the panel data should be properly examined. Traditional time series unit root tests method involves the low power problem for nonstationary data. The primary motivation for panel data unit root tests is to take advantage of the additional information provided by the pooled cross-section time series to increase power of the traditional tests (Maddala and Wu 1999). We use Fisher type panel unit root tests to test nonstationarity of the variables. In this regard, we follow the procedures developed first by Maddala and Wu (1999) and Choi (2001). In addition, we perform panel unit root test developed by Im-Pesaran-Shin (IPS) (Im et al. 2003) to enhance the robustness of the results. Results of unit root tests are reported in Table 2. Panel unit root test results indicate that for all the series in levels except pesticide consumption per hectare and population growth, we reject the null hypothesis of nonstationarity. Nevertheless, all the variables which are nonstationary at levels turn stationary in first difference. Therefore, we take first difference of all the nonstationary variables before estimation. However, model employed in first difference is a short run model (rather than a long run model) and that the estimated coefficients, rather than being elasticities, are constants of proportionality between percentage changes in the independent variables and percent changes in the dependent variable (Liddle 2014).

In order to test whether the factors considered in the *STIRPAT* model influence the level of fertilizer and pesticide consumption, we have used empirical model derived in Sect. 2 Eqs. (7, 8). The econometric methods employed here to estimate the models take into account the unbalanced nature of panel data which we have at our disposal. Table 3 reports the estimated results. We start by estimating fixed effects (FE) and random effects (RE) model which controls unobserved state effects which may influence the dependent variable. The FE results reported in the table assume that each state starts from different levels of pesticide and fertilizer consumption. With respect to random effects, we have applied the Hausman test in order to test the orthogonality between the unobserved effects and regressors. Hausman test results indicate that only coefficients of model specified with fixed effects (FE) give consistent estimates.

Table 2 Panel unit root test results

Variable	Fisher-ADF	Fisher-PP	IPS
ln(FERTH)			
Level			
Individual effects	38.32	57.87	1.12
Individual effects with time trends	90.87***	126.02***	−1.70**
First difference			
Individual effects	433.68***	603.46***	−13.63***
Individual effects with time trends	199.25***	252.69***	−6.36***
ln(PESTH)			
level			
Individual effects	79.73***	86.84***	−1.66**
Individual effects with time trends	122.06***	121.14***	−3.90***
ln(NSDPPC)			
level			
Individual effects	7.33	9.12	9.87
Individual effects with time trends	98.47***	124.62***	−5.52***
First difference			
Individual effects	189.71***	225.12***	−9.76***
Individual effects with time trends	169.66***	238.52***	−6.34***
$(ln(NSDPPC))^2$			
level			
Individual effects	7.04	8.74	10.32
Individual effects with time trends	94.20***	117.96***	−6.14***
First difference			
Individual effects	182.65***	211.92***	−9.35***
Individual effects with time trends	166.90***	235.87***	−6.22***
ln (PP)			
level			
Individual effects	34.79	42.83	2.38
Individual effects with time trends	113.74***	165.78***	−2.19**
First difference			
Individual effects	206.53***	517.45***	−10.41***
Individual effects with time trends	176.43***	222.80***	−7.72***
POPG			
level			
Individual effects	129.52***	100.03***	−6.00***
Individual effects with time trends	137.23***	142.26***	−6.59***
ln (IRS)			
level			
Individual effects	62.33	82.17***	−0.78
Individual effects with time trends	69.72**	88.31***	−1.00
First difference			
Individual effects	268.99***	346.65***	−13.06***

Table 2 continued

Variable	Fisher-ADF	Fisher-PP	IPS
Individual effects with time trends	186.96***	249.73***	−5.70***

Fisher-ADF and Fisher-PP represent test proposed in Maddala and Wu (1999) and Choi (2001), respectively

IPS represents the panel unit root test of Im et al. (2003)

Probabilities for Fisher type tests are computed by using an asymmetric Chi-square distribution

IPS, Fisher-ADF, and Fisher-PP tests examine the null hypothesis of nonstationarity

*** and ** indicates statistical significance at the 5 and 10 % level, respectively

Table 3 Regression results for fertilizer and pesticide consumption

	Fertilizer consumption per hectare			Pesticide consumption per hectare		
	FE	RE	FE (DK)	FE	RE	FE (DK)
lnNSDPPC	−6.13*	−1.74	−6.13***	28.39**	27.64**	28.39**
	(3.52)	(2.85)	(1.55)	(10.96)	(11.05)	(11.67)
(lnNSDPPC)^2	0.32*	0.09	0.32***	−1.50***	−1.46**	−1.50**
	(0.18)	(0.14)	(0.08)	(0.57)	(0.57)	(0.61)
lnPOP	0.58*	0.64**	0.58***	−0.88	−0.83	−0.88**
	(0.31)	(0.31)	(0.18)	(0.96)	(0.98)	(0.34)
lnIRS	0.19***	0.16**	0.19**	0.02	0.05	0.02
	(0.06)	(0.06)	(0.08)	(0.21)	(0.21)	(0.19)
PG	0.03***	0.006	0.03**	0.02	0.008	0.02
	(0.01)	(0.007)	(0.01)	(0.03)	(0.03)	(0.04)
Constant	−0.05**	0.007	−0.05	−1.73***	−1.84***	−1.73***
	(0.02)	(0.01)	(0.02)	(0.07)	(0.17)	(0.07)
R^2	0.03	0.04	0.09	0.03	0.01	0.03
Hausman:χ^2		21.36			174.23	
		(5)***			(5)***	
Modified wald:χ^2	1,235.24			70,813.54		
	(25)***			(25)***		
Wooldridge: F	16.64			32.28		
	(1,23)***			(1,23)***		
Income turning point		INR 14445.31				INR 12909.95

FE fixed effects, *RE* random effects, *FE* (*DK*) fixed effect estimates with Driscoll–Kraay standard errors. Modified wald: χ^2 test for group-wise heteroskedasticity. Wooldridge: *F* test for serial correlation in panel data. Standard errors of estimates are in parenthesis. *, **, *** refers to significance at 10, 5, and 1 % level. In the case of diagnostic tests, figures in parentheses refer to degree of freedom

For variables like GDP per capita and agrochemical use in agriculture, cross-sectional dependence is likely because of, for example, regional and macroeconomic linkages that manifest through common shocks like floods and droughts. Disregarding cross-sectional correlation in panel data models can lead to incorrect inferences (Beck and Katz 1995, 1996). However, converting variables to first differences can address cross-sectional dependence (Liddle 2014). Additionally, group-wise heterogeneity may be a problem due to unbalanced structure of panel data (Ghimire and Woodward 2013). Serially correlated errors may also bias the estimates, and the inference drawn may be incorrect. The modified Wald test (Greene 1993; Baum 2001) result indicates that FE model results suffer from

Table 4 Achievements of integrated pest management (IPM) in India (1994–2008)

IPM trainings and demonstrations	Farmers field schools (numbers)	12,931
	Agriculture extension officers to be trained (numbers)	54,349
	Farmers to be trained	3,88,863
IPM achievements	Pest monitoring	12.38 million Hectare
	Field releases of biocontrol agents	27,574 million

Source: Directorate of plant protection, quarantine, and storage, Government of India

group-wise heteroskedasticity. Similarly, using the Wooldridge test (Wooldridge 2002) for autocorrelation, we reject the null hypothesis of no first order autocorrelation.[4]

To correct the problems, we estimate FE model using Driscoll and Kraay (1998) methodology which applies a Newey–West type correction to the sequence of cross-sectional averages of moment condition. Adjusting the standard error in this way, Driscoll and Kraay's approach eliminates the deficiencies of other estimators such as the feasible generalized least square method (Parks 1967) and PCSE method (Beck and Katz 1995, 1996) which become inappropriate when the cross-sectional dimension of the panel gets large (Hoechle 2007).

Results obtained for fertilizers model confirm a *U*-shaped relationship between fertilizer consumption per hectare and NSDP per capita. An increase in 1 % in per head NSDP causes 6.13 % decline in per hectare fertilizer consumption before a threshold per capita GDP is achieved. Beyond threshold level of per capita GDP, every 1 % change in per capita NSDP causes 0.32 % increase in per hectare fertilizer consumption. Population variables, population pressure on agriculture and population growth, show a significant positive relationship with fertilizer consumption per hectare. Share of agricultural land which receivers irrigation is also positively related to per hectare fertilizer consumption. This result is on expected lines similar to those found in other studies.

The pesticide model shows very different results. Estimated coefficients in pesticide model indicate an inverted *U*-shaped relationship between pesticide consumption per hectare and per capita NSDP showing that pesticide consumption per hectare increases first and then may decline with economic growth. While the inverted *U* for pesticide use is supported by other studies also; turning point in case of present study turns very low (INR 12909.95) in comparison (see Longo and York 2008; Li et al. 2014). According to the estimates, per hectare pesticide consumption is negatively related to the population pressure on agriculture land, i.e., states having more population pressure on agricultural land is using pesticides less intensively. Longo and York (2008) in a cross-sectional study observed a positive relationship between total pesticide consumption and population. Another study by Ghimire and Woodward (2013) observes a quadratic relationship between agriculture land per capita and pesticide use per hectare. Result in present study seems convincing considering the fact that chemical pesticide exposure has immediate and sometimes lethal impact on human and livestock population.

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[4] Wooldridge procedure regresses the residuals from the regression with first differenced variable on their lags and tests that the coefficient on the lagged residual is equal to -0.5. Central to this procedure is the observation, that if residuals are not serially correlated then correlation between residual and its lagged value is -0.5.
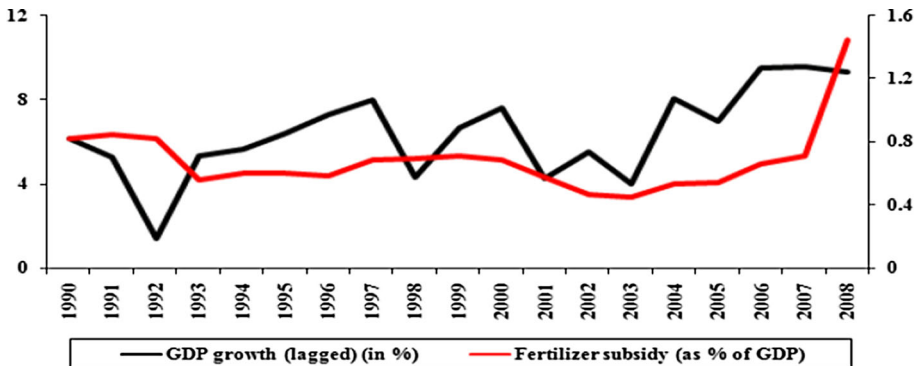
Fig. 5 Fertilizer subsidies and GDP growth in India (1990–2008). *Source*: Authors own compilation

It is well established in previous research that relationship between a potential pollutant and per capita income may take various shapes and is more likely to hold an inverted *U* for short-term and local impact pollutants than for those with long-term impacts (Grossman and Kruger 1995). In addition, observed relationship between income and agrochemicals use in the present study does not show a steep slope after income turning point occurs rather it indicates a flattening out of the relationship in case of both fertilizers and pesticides. Fertilizers, unlike pesticides which have immediate impact on human/livestock health, have long run impact on agricultural environment. It is widely believed that long run pollutants which do not have an immediate impact on economic activities do not attract immediate policy response (Dasgupta et al. 2002). In addition, considering importance of fertilizers to sustain food production and increasing government support to fertilizers use with rising prosperity, a *U*-shaped fertilizer income curve is not unexpected. In addition, effect of increasing food demand due to rising income also cannot be ignored as a factor explaining a rise in fertilizer consumption per hectare after per capita income reaches a threshold.

Rationalization of agricultural subsidies to achieve targeted fiscal deficit first during structural adjustment (1991–1996) and later under fiscal reform initiatives of the central government seems to be a major reason behind declining per hectare fertilizer consumption in India during 1990s. Figure 5 shows that fertilizer subsidies as a percent of GDP fell drastically in 1992–1993; however, an upward shift can be observed in subsidy GDP ratio in 1996–1997 and in 2003–2004. Furthermore, line plot of lagged (by 1 year) GDP growth clearly shows that increase in fertilizer subsidy (as a percent of GDP) went hand in hand with economic growth in India.

Inverted *U* for pesticides may be interpreted as follows: First, emerging trend could be an outcome of the decline of agricultural sector due to structural change (Brock and Taylor 2005). Importance of structural change to explain declining pesticide IU is also highlighted in previous section. Decline in agriculture growth does not seem to play an important role in case of fertilizers because of the existing fertilizer subsidies; however, it becomes important in case of pesticides because no support is provided by the government for promoting use of chemical pesticides. Second, awareness created through stringent government regulations against pesticides and wide media coverage to pesticide deaths may be a reason restraining farmers to use pesticides more intensively. Third, area under better management practices such as integrated pest management (IPM) (Table 4) and use of
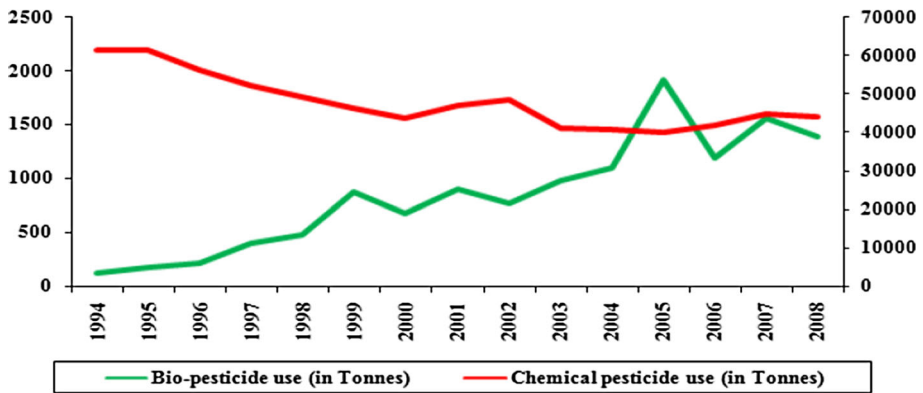
Fig. 6 Consumption of biopesticides and chemical pesticides in India (1994–2008). *Source*: Directorate of plant protection, quarantine, and storage, Government of India

biopesticides (Fig. 6) has been increasing continuously in India.[5] Expanding IPM activities and use of biopesticides may be another reason for a flattened pesticide income curve after reaching a peak. It is evident that expansion of pest management program and better management practices are dependent on government supports which in turn determined by economic prosperity.

5 Conclusion

We have conducted a multivariate analysis on the determinants of agrochemical use in the Indian states during the period 1990–2008. We have adopted Dietz and Rosa (1997) formulation as our theoretical framework. In their model, population is introduced as a predictor, together with affluence. We have modified the framework by considering per hectare agrochemical use as a measure of impact. Accordingly, we use population per hectare of agricultural land as a predictor instead of population. We find evidence in support of the hypothesis that a nonlinear relationship exists between agrochemical use and per capita NSDP in India and provide evidence that population have a significant impact on agrochemical use. As a whole, the increase in income and population pressure on agricultural land seems to be the driving forces determining use of agrochemicals. A few implications can be drawn from the results which may be useful from the policy point of view.

States where agriculture is the main occupation and which are lagging behind in terms of economic growth, agriculture-related environmental issues should be attached more importance. In addition, if fertilizer consumption per hectare is associated with the change in subsidies which seem to be the case in India then more rational distribution of fertilizer subsidies across states is needed as distribution of per hectare fertilizer consumption is skewed toward few rich states and big farmers. In this connection, policy of transferring

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[5] Integrated Pest Management (IPM) is an eco-friendly approach which uses cultural, mechanical and biological tools and techniques for keeping pest population below economic threshold levels. This approach attaches a high premium on the efficacy of bio-control agents and bio-pesticides. However, need based and judicious use of chemical pesticides is permitted.

cash subsidy to farmers may help to bring parity among states as far as fertilizer consumption is concerned. To improve the efficiency of fertilizer use, soil tests at regular intervals are mandatory. Few states in India such as Gujarat have institutionalized soil testing mechanisms; however, farmers in economically backward states are still devoid of institutionalized soil testing facilities. In this regard, economic growth, by providing resources to manage agriculture-related environmental problems, becomes an important factor determining level of agrochemical use and agricultural pollution.

A caveat to empirical data-based exercises is that sometimes they present a simplified picture to a rather complex relationship. Relationship between agrochemical use and economic growth is complex and many faced. A favorable relationship (inverted U) does not mean that degradation of agricultural resources and agricultural pollution is a temporary phenomenon associated with some stages of economic growth and will naturally decrease with increasing economic growth. Relatively small coefficient value for squared income term in pesticide model suggests that pesticide use may take any direction according to the change in government policies and demand for agriculture products. In this connection, there is a need to increase the reach and effectiveness of integrated pest management program in India, especially use of biopesticides can be encouraged by subsidizing it.

Appendix

See Tables 5, 6 and 7.

Table 5 Summary of variables

	Mean	Min	max	Standard deviation	Skewness	Kurtosis	JB test statistics
PESTH	0.27	0.02	0.98	0.25	1.28	3.67	374.7***
NPKH	74.19	1.92	215.73	52.58	0.62	2.41	101.8***
NSDPPC	17875.19	5994.00	56021.00	7399.79	1.61	6.94	1.7e+06***
POP/H	7.04	2.13	15.40	3.49	0.72	2.33	27.31***
PG	1.97	−0.67	12.03	1.12	3.46	24.84	36.3***
IRS	36.26	2.76	98.21	22.72	1.17	3.53	83.21***

Summary statistics (except Jarque-Bera test) is generated before taking logarithm of variables

Table 6 Correlation matrix

	PESTH	NPKH	NSDPPC	POP/H	PG	IRS
PESTH	1.00					
NPKH	0.64	1.00				
NSDPPC	0.25	0.36	1.00			
POP/H	−0.05	0.16	0.14	1.00		
PG	−0.04	−0.07	−0.03	−0.07	1.00	
IRS	0.69	0.76	0.19	0.02	−0.01	1.00

Table 7 Panel cointegration test results

	Fertilizer model		Pesticide model	
	NDT	DIT	NDT	DIT
Panel v-statistic	0.84	−0.7	−2.15	−3.16
Panel rho-statistic	1.06	3.02	3.61	4.37
Panel PP-statistic	−10.17***	−6.77***	−7.29***	−13.00***
Panel ADF-statistic	−9.74***	−6.10***	−7.45***	−8.85***
Group rho-statistic	3.98	5.01	5.24	5.59
Group PP-statistic	−17.34***	−17.92***	−16.35***	−16.57***
Group ADF-statistic	−8.01***	−6.12***	−8.40***	−8.53***

For the formulas used in the panel cointegration test statistics, it is described in detail in Pedroni (1999). The panel ADF-statistic, group ADF-statistics, panel PP-statistic, and group ADF-statistic tests have better small sample properties than the others and hence they are more reliable. Statistics are asymptotically distributed as normal. *NDT* stands for no deterministic trend, and *DIT* stands for deterministic intercept and trend. *** rejects the null of no cointegration at the 1 % level

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