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Impact of natural resource management technologies on technical efficiency in sorghum cultivation: application of meta-frontier and endogenous switching regression model

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Abstract This study assesses the impact of the adoption of natural resource management (NRM) technologies on sorghum production in the drought-prone areas of Indian state of Karnataka, using plot-level data. The key factors affecting adoption are access to credit, extension services, and social networks. The bias-corrected technical efficiency scores and the meta-technology ratio indicate that efficiency can be improved by 30%. The result of endogenous switching regression shows that the average treatment effect on treated is -0.24, suggesting a 13%. reduction in production efficiency. Adopting NRM technologies could enhance production and farmer livelihoods in drought-prone areas.

Keywords Impact assessment, natural resource management, sorghum, meta-frontier

JEL codes Q01, Q5, Q15

Soil degradation (Biswas et al. 2019) and climate change (Krishnakanth and Nagaraja 2020) threaten agricultural sustainability in Karnataka, one of the most drought-prone states of the country (Nagaraja, Somashekar, and Kavitha 2011). Severe to moderate droughts are frequent in Karnataka (Ray et al. 2015; KSNDMC 2017); more than 70% of the cultivated area is rainfed, and the droughts often result in partial or complete crop failure (Biradar and Sridhar 2009).

The crop production potential is limited also by erratic and uncertain rainfall, with higher degree of spatial temporal variability; depleting groundwater resources; inadequate infrastructure; low input use and technology adoption; and eroding natural resources. The average yield of most common crops is between two and five times less than their optimal yield level (Wani et al. 2011). The crop loss due to water erosion alone is INR 32,429 million (at 2014–15 prices), the second highest in the country after Madhya Pradesh (TERI 2018).

Natural resource management (NRM) technologies enhance productivity by conserving soil moisture, improving soil health, and encouraging the use of quality inputs and improved seeds (Kerr and Sanghi 1992; Gebrernichael et al. 2005; Rajkumar and Satishkumar 2014; Bhattacharyya et al. 2015; Wolka, Mulder, and Biazin 2018). The NRM technologies recommended in the region are broad bed and furrow, contour bunding, graded bunding, compartment bunding, ridges and furrows, contour cultivation, and set-furrow cultivation (Pathak, Laryea, and Singh 1989; Vittal et al. 2004; Sharma and Guled 2012; Mishra, Singh, and Kumar 2018).

Contour bunding is the most widely practised technique in the semi-arid tropics (Bhattacharyya et al. 2015; Narayan, Biswas, and Kumar 2019; Naveena, Shivaraj, and Nithin 2019; Pathak et al. 1989). Soil bunds help in reducing soil loss and run-off and in improving soil moisture and fertility and, in turn, increasing crop productivity (Gebrernichael et al. 2005; Kerr and

Sanghi 1992; Rajkumar and Satishkumar 2014). Using soil bunds positively influences crop productivity.

The state government has been trying to scale the adoption of conservation technologies, but private or voluntary adoption has been low (Reddy, Hoag, and Shobha 2004; Bhattacharyya et al. 2015), and there is a need to understand the factors that affect the adoption of conservation technologies and their effect on production performance. Few studies have used plot-level data and the meta-frontier approach to compare the technical efficiency (TE) of adopters and non-adopters in India, however, to the best of our knowledge.

This study assesses the impact of the soil bunds technique on efficiency and explores the linkages between NRM and technical efficiency (TE). We use the endogenous switching regression (ESR) model to control for the heterogeneity effects of observed and unobserved factors. To estimate the bias-corrected TE scores, we use the double bootstrap data envelopment analysis (DEA) technique (Simar and Wilson 2007). To identify the factors affecting the TE for each group, we use bootstrapped regression.

This paper will help policymakers to design programmes for increasing the adoption rate of NRM technologies and, thereby, sustain the natural resources and livelihoods of resource-poor farmers in the region.

Data and study area

We purposively selected a region of Karnataka that is a drought hotspot and where the frequency of drought is projected to increase in the future (BCCI-K 2011). We randomly selected four districts—Tumukuru, Koppal, Bidar, and Gadag—as first-stage sampling units. At the second stage, we selected a sub-watershed from each district. From each watershed (treated area), we randomly selected plots from net planning reports (a net planning report forms part of a detailed project report/feasibility report, which contains information on all the plots of the farmers in a watershed). Sorghum is an important food and fodder crop in drought-prone areas; this way, we chose 193 sorghum-growing plots for a detailed survey (including household-level features), and we also randomly selected 251 control plots (untreated areas) in the vicinity of treated areas. The variables selected for this study are guided by the relevant literature and the understanding of watershed management in the region.

Methodology

Generally, to estimate TE, the two-step DEA approach is used, but Simar and Wilson (2007) argue that it does not account for the underlying data-generating process (DGP), and its efficiency estimates are serially correlated and these lead to statistically invalid inferences. The implication is that the efficiency estimates of the two-step DEA approach are biased, and these positively exaggerate the level of efficiency within a sample.

Double bootstrap data envelopment analysis (DEA) method

In the double bootstrap DEA method, the estimates of efficiency scores are bias-corrected–the idea underlying bootstrapping is simply to simulate the sampling distribution of interest by mimicking the DGP—and policymakers can view the results with more confidence. Therefore, we use the double bootstrap DEA method.

$$TE_j = min\{: \delta X_J \in L(Y_j)\}$$

$$TE_j = \min_{\delta,\lambda} \delta$$

St $\sum_{j=1}^{n} \lambda_{kj} y_{kj} \geq y_{ko}$

$$\sum_{j=1}^{n} \lambda_{kj} x_{mkj} \leq \delta x_{mko} \; \forall \; m$$

The DEA can be formulated with the assumption of either constant returns to scale (CRS) $\lambda_{kj} \geq 0$ or variable returns to scale (VRS) $\Sigma_{j=1}^{n} \lambda_{kj} = 1$, $\lambda_{kj} \geq 0$. Similarly, we can define an input-oriented DEA for meta-frontier efficiency estimation and use a bootstrapping technique to correct biased efficiency scores (δ_{kj}):

$$\hat{b}_k = \frac{1}{T} \sum_{t=1}^{T} \delta_{kj}^{*(T)} - \delta_{kj}$$

Where $\hat{b}_k$ is bias, the bias-corrected TE scores can be given as

$$\bar{\bar{\delta}}_{kj} = \delta_{kj} - \hat{b}_k$$

Estimation of meta-frontier efficiency

The meta-frontier is 'the envelope of commonly conceived classical production functions' (Hayami and Ruttan 1971). The meta-frontier model groups all farmers by their level of adoption. The model indicates the sources of technological heterogeneity and enables the estimation of comparable technical efficiencies for firms operating under different technologies (Battese, Rao, and O'Donnell 2004).

The meta-frontier is an envelope—it considers all the group frontiers (Moreira and Bravo-Ureta 2010; Le, Vu, and Nghiem 2018)—therefore, the TE estimated employing the meta-frontier model is lower than the TE estimated using the group-specific frontier. One implication is that there exists a non-negative distance—known as the meta-technology ratio (MTR), and defined as the 'gap in technology access to a given group relative to technology available to all groups taken together, i.e. global or meta-frontier efficiency'.

Higher the value of the MTR, less the gap between the group frontier and the meta-frontier (O'Donnell, Rao, and Battese 2008). Therefore, there is a need to shift to a higher-MTR technology or group or increase production by switching to a higher-MTR group.

$$MTR^k(.) = \frac{\bar{\bar{\delta}}_G}{\bar{\bar{\delta}}_K}$$

where, $\bar{\bar{\delta}}_G$ is bias-corrected meta-frontier or global TE, and $\bar{\bar{\delta}}_K$ is bias-corrected group-specific TE.

Determinants of technical inefficiency

Efficiency scores are not generated by a censoring DGP but are fractional data-generating processes; therefore, it is not appropriate to use Tobit to explain the determinants of efficiency (Banker and Natarajan 2008; McDonald 2009). Unbiased parameter estimates can be yielded by bootstrapped truncated regression:

$$\bar{\bar{\delta}}_{kj} = \alpha + Z_j\phi + \mu_j;\ j=2;\ \mu_j \sim N(0,1)$$

Where,

$\bar{\bar{\delta}}_{kj}$ = group-specific efficiency

Z_j=set of variables expected to be influencing efficiency

Endogenous switching regression model for impact assessment

The decision to adopt NRM technologies is a standard dichotomous choice model assuming that the farmer is risk-neutral and they compare the net benefit from the NRM technologies in making their decision. Assume that TIE_{iNRM} indicates the technical inefficiency—the inverse of technical efficiency—of a farmer with the adoption of NRM technologies, TIE_{iNA} indicates technical inefficiency with non-adoption, and a farmer will choose NRM if $TIE_{iNRM} < TIE_{iNA}$.

$$\text{Adopter: } TIE_{iNRM} = X_i\beta_{NRM} + \mu_{iNRM}\,;\ \mu_{iNRM} \overset{iid}{\rightarrow} N(0,1) \quad \text{... (1)}$$

$$\text{Non-adopter: } TIE_{iNA} = X_i\beta_{NA} + \mu_{iNA}\,;\ \mu_{iNA} \overset{iid}{\rightarrow} N(0,1) \quad \text{... (2)}$$

where, X_i is a vector of explanatory variables including personal and household-level characteristics, plot features, perception (risk of crop failure and benefits of NRM technologies), inputs of crop production, and other institutional variables; β_{NRM} and β_{NA} are vectors of parameters to be estimated.

Assume that T_i^* is a latent variable that indicates that adopting NRM technologies yield positive net benefits. It can be expressed as a function of farmers' characteristics, say W, as given below:

$$T_i^* = \gamma' W + \varepsilon_i;\ \varepsilon_i \overset{ND}{\rightarrow} (0, \sigma_\varepsilon^2)$$

$$T_i = 1 \text{ if } T_i^* > 0$$

$$T_i = 0 \text{ if } T_i^* < 0 \quad \text{...(3)}$$

where, T_i^* is a dichotomous variable, taking value 1 for the adopter of NRM technologies and 0 for non-adopters. The γ' is a vector of parameters to be estimated. The captures measurement errors as well as unobservable factors influencing technical inefficiency.

This study aims to estimate the impact of the adoption of NRM technologies on TE; however, in cross-section data, there is a problem of counterfactuals–the baseline data for adopters is absent. Another problem is the selection bias, which stems from the inability to observe the managerial and technical abilities of farmers (Abdulai and Huffman 2014). If the unobservable factors influence the error terms of outcome (μ_i) and selection equation (ε_i), the influence will lead to a non-zero correlation coefficient—corr(ε,μ) = $\rho \neq 0$—and the estimates of the ordinary least squares method will be biased.

In assessing impact, dealing with selection bias is critical; therefore, to examine the determinants of the adoption of NRM technologies and the impact of adoption on technical inefficiency, we employ the endogenous regime switching(ERS) model—a parametric approach that accounts for selection bias from observed as well as unobserved variables (Maddala 1986). To capture the differential impact in the ESR model, we group all the observations by adopters of NRM technologies and non-adopters. Two regimes can be given as follows:

Regime 0: $TIE_{iNA} = X_i\beta_{NA} + \mu_{iNA}$; $T_i = 0$

Regime 1: $TIE_{iNRM} = X_i\beta_{NRM} + \mu_{iNRM}$; $T_i = 1$ …(4)

Are Equations 1, 2, and 4 the same? In Equations 3 and 4, all the variables could be the same, but for the identification of the selection equation from the outcome equations, there should be at least one variable (instrumental variable, IV) *W* in which is not included in *X*. When there is non-zero correlation between the error terms ..... and μ_{iNRM}, μ_{iNA}, these error terms follow a trivariate normal distribution with zero mean and variance and covariance matrix (Lokshin and Sajaia 2004):

$$\Omega = \begin{bmatrix} \sigma^2_{NRM} & \sigma_{NRM,NA} & \sigma_{NRM,\varepsilon} \\ \sigma_{NRM,NA} & \sigma^2_{NA} & \sigma_{NA\varepsilon} \\ \sigma_{NRM,\varepsilon} & \sigma_{NA,\varepsilon} & \sigma^2_{\varepsilon} \end{bmatrix} \quad \dots(5)$$

where, the diagonal terms are variances and off-diagonal terms are co-variances. The selection bias arising due to observable variables is taken care of in Equation 4, but we need to estimate and test the inverse Mills ratio (IMR) for both adopters and non-adopters for selection bias from the unobserved variables. The expected values of truncated error can be obtained as follows:

$$E(\mu_{NA}|T=0) = \sigma_{NA\varepsilon}\frac{-\emptyset(\frac{W'\gamma}{\sigma})}{1-\Phi(\frac{W'\gamma}{\sigma})} \equiv \sigma_{NA\varepsilon}\lambda_{NA} \quad \dots(6)$$

$$E(\mu_{NRM}|T=1) = \sigma_{NRM\varepsilon}\frac{-\emptyset(\frac{W'\gamma}{\sigma})}{1-\Phi(\frac{W'\gamma}{\sigma})} \equiv \sigma_{NRM\varepsilon}\lambda_{NRM} \quad \dots(7)$$

where, ϕ is the standard normal probability density (PDF) function and Φ is the standard normal cumulative distribution function (CDF). λ_{NA} is the IMR for non-adopters and λ_{NRM} is the IMR for adopters, representing selectivity. To account for selectivity bias, IMRs are added in Equation 8:

Regime 0: $TIE_{iNA} = X_i\beta_{NA} + \sigma_{NA\varepsilon}\lambda_{NA} + \mu_{iNA}$; $T_i = 0$

Regime 1: $TIE_{iNRM} = X_i\beta_{NRM} + \sigma_{NRM\varepsilon}\lambda_{NRM} + \mu_{iNRM}$; $T_i = 1$ …(8)

The residuals in the two-stage estimation method are heteroscedastic, and it is difficult to get consistent standard errors without performing a complex weighting procedure (Lokshin and Sajaia, 2004); therefore, we use the full information maximum likelihood estimation (FI-MLE) method for the simultaneous estimation of the selection and outcome equations. Moreover, the FI-MLE method yields consistent and asymptotically efficient parameters (Maddala, 1986), and the signs and significance levels of the correlation coefficient of the error terms between the selection and outcome equations have an economic interpretation.

If $\rho_{NA\varepsilon}$ and/or $\rho_{NRM\varepsilon}$ is significantly different from 0, the presence of selectivity bias is indicated, and the use of ESR is appropriate. If $\rho>0$, the selection bias is negative; it indicates that farms at above-average technical inefficiency are less likely to adopt NRM technologies. If $\rho<0$, the selection bias is positive; it indicates that farms at below-average technical inefficiency are more likely to adopt NRM technologies (Abdulai & Huffman, 2014). If the correlation coefficients have the same sign, hierarchical sorting is indicated: adopters have below-average technical inefficiency compared to non-adopters—irrespective of the adoption decision. An alternate sign indicates that farmers adopt NRM technologies according to comparative advantage (Alene and Manyong 2007). The expected value of outcome for an adopter is given by:

$$E(TIE_{NRM}|T=1) = X_i\beta_{NRM} - \sigma_{NRM\varepsilon}\lambda_{NRM} \quad \dots(9)$$

Term $\sigma_{NRM\varepsilon}\lambda_{NRM}$ shows sample selectivity, indicating that farms that adopted NRM technologies may behave differently from average farms with identical features because of unobserved variables (Maddala 1986). If the same farm had not adopted NRM technologies, the expected outcome would have been

$$E(TIE_{NA}|T = 1) = X_i\beta_{NA} - \sigma_{NA\varepsilon}\lambda_{NRM} \quad \ldots(10)$$

Now, the average treatment effect on the treated (ATT) can be given (Lokshin and Sajaia 2004):

$$ATT = E\,(TIE_{NRM}|T = 1) - (TIE_{NA}|T = 1) = X_i(\beta_{NRM} - \beta_{NA}) + \lambda_{NRM}\,(\sigma_{NRM\varepsilon} - \sigma_{NA\varepsilon}) \quad \ldots(11)$$

Similarly, the average treatment effect on the untreated (ATU) can be given:

$$ATU = E\,(TIE_{NRM}|T = 0) - (TIE_{NA}|T = 0) = X_i(\beta_{NRM} - \beta_{NA}) + \lambda_{NA}\,(\sigma_{NRM\varepsilon} - \sigma_{NA\varepsilon}) \quad \ldots(12)$$

Further, the base heterogeneity effects can be estimated:

$$BH_1 = E\,(TIE_{NRM}|T = 1) - E(TE_{NRM}|T = 0) \quad \ldots(13)$$

$$BH_2 = (TIE_{NA}|T = 1) - E(TE_{NA}|T = 0) \quad \ldots(14)$$

Results and discussion

There is no difference between adopters and non-adopters on most household-level characteristics (except the number of livestock units, access to credit, and off-farm income) (Table 1). The number of livestock units is higher for adopters than non-adopters because the availability of fodder is better in treated areas—soil bunds are stabilized by growing grass species, which supply additional fodder (Arya, Panwar, and Yadav 2011). Also, project implementing agencies (PIA) distribute cross-breed cows in watershed areas. Higher access to credit also can be attributed to efforts made by PIAs to create awareness about ongoing financial assistance schemes and link farmers in self-help groups (SHG) to formal banks.

In the case of plot-level features, adopters differ from non-adopters in terms of slope, soil erosion, and fertility levels. The plots of around 90% of non-adopters and 64% of adopters had a high slope and soil erosion was high. The perception of the risks of crop failure and the benefits of conservation technologies differed between adopter and non-adopter farms. Extension and training services officers had conducted more exposure visits and training programmes for adopter farmers than non-adopters, because before watershed activities are executed—and in the capacity-building phase—PIAs try to persuade farmers of the benefits of NRM technologies by taking them to visit model watersheds, and they conduct training programmes during the phases of watershed development. At the time of watershed activities, many committees and groups are formed for the effective execution of conservation measures, and the social networks of adopter farmers are better than that of non-adopters. Further, the input utilization of adopters is statistically different than that of non-adopters.

Distribution of technical efficiency

The mean group-specific technical efficiency (GSTE) is 0.83 for adopters and 0.84 for non-adopters (Table 2). The meta-frontier technical efficiency (MFTE) is 0.68 for adopters and 0.53 for non-adopters. The MFTE is less than the GSTE because, in the case of the GSTE, an individual farm faces only the group frontier but, in the case of the meta-frontier, the farm is compared with the global frontier. The MTR for adopters is 0.82, higher than the 0.63 for non-adopters, and it shows that a shift in technology can enhance efficiency by 30.16% (Table 2).

The two-sample Kolmogorov–Smirnov test rejected the CRS model (0.61712, p-value <0.00); therefore, we discuss the results of the VRS model. Moreover, with the plot-level data, the VRS model seems more realistic than the restrictive CRS model. The frequency distribution of the GSTE shows that the efficiency scores of around 79% of the adopter plots and 84% of the non-adopter plots lie in the 70–100% range. The efficiency score exceeds 90% for around 46% of the adopter plots and 42% of the non-adopter plots in the GSTE (Table 3).

Factors affecting technical inefficiency

The results of the factors affecting the technical inefficiency of sorghum production (Table 4) show that age, dependency ratio, number of livestock units, farm assets index and access to credit are associated with less technical inefficiency; these factors enhance production efficiency. The farm assets index shows the ownership of farm implements; farmers who rank high on the higher farm assets index can carry out agricultural operations in time, particularly at critical growth stages, which in turn positively affects efficiency. Our results are in line with Vortia et al. (2019), which reports a positive relationship between farm mechanization and efficiency. Access to credit has a positive and statistically significant effect on efficiency as it enables farmers to utilize improved or new technologies and a better mix of quality inputs for crop production (Laha 2013).

Table 1 Sample plots (descriptive summary)

		Sample (N=444)	Adopter (N=193)	Non-Adopters (N=251)	p-value
Household-level characteristics					
Head (male=1; otherwise 0)		0.82(0.39)	0.79 (0.41)	0.84 (0.37)	0.269
Age (years)		50.0 (12.3)	50.2 (11.7)	49.8 (12.8)	0.717
Education (number of schooling years)		5.3 (4.5)	5.3 (4.3)	5.3 (4.6)	0.983
Family size (number of members)		5.1 (1.8)	5.1 (1.8)	5.0 (1.8)	0.716
Size of landholding (ha)		2.5 (2.0)	2.4 (1.9)	2.5 (2.1)	0.903
Livestock (number of animals)		4.0 (2.7)	5.0 (2.9)	4.0 (2.5)	0.001
Off-farm income (if yes=1; otherwise 0)		279 (62.8)	166 (86.0)	113 (45.0)	<0.001
Dependency ratio (area per capita)		0.5 (0.5)	0.5 (0.4)	0.5 (0.5)	0.601
Farm asset index#		0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.902
Access to credit		271 (61.0)	144 (74.6)	127 (50.6)	<0.001
Farm-/plot-level characteristics					
Size of plots		0.8 (0.6)	0.8 (0.6)	0.8 (0.5)	0.562
Number of plots		3.0 (1.9)	3.1 (2.1)	2.9 (1.7)	0.281
Tenure (if own=1; otherwise 0)		310 (69.8)	129 (66.8)	181 (72.1)	0.273
Slope of plot (if high=1; otherwise 0)		309 (69.6)	174 (90.2)	135 (53.8)	<0.001
Type of soil (if red=1; otherwise 0)		137 (30.9)	72 (37.3)	65 (25.9)	0.013
Type of soil (if black=1; otherwise 0)		208 (46.8)	92 (47.7)	116 (46.2)	0.835
Soil erosion perception (if high=1; otherwise 0)		262 (59.0)	124 (64.2)	138 (55.0)	0.061
Soil erosion perception (if medium=1; otherwise 0)		92 (20.7)	37 (19.2)	55 (21.9)	0.556
Fertility of plot (if high=1; otherwise 0)		178 (40.1)	96 (49.7)	82 (32.7)	<0.001
Fertility of plot (if medium=1; otherwise 0)		246 (55.4)	89 (46.1)	157 (62.5)	0.001
Perception of farmers					
Risk perception (chances of crop failure)		4.8 (1.4)	5.4 (1.5)	4.3 (1.1)	<0.001
Benefit perception index# (number)		3.3 (0.7)	3.2 (0.7)	3.4 (0.7)	0.01
Extension and training services					
Number of visits of KVK and RSK		3.0 (1.6)	3.0 (1.5)	3.0 (1.6)	0.731
Exposure visits (If yes=1; otherwise 0)		1.1 (0.9)	1.5 (0.8)	0.8 (0.9)	<0.001
Training (If yes=1; otherwise 0)		284 (64.0)	144 (74.6)	140 (55.8)	<0.001
Social network					
Interaction	1= sometimes	152 (34.2)	43 (22.3)	109 (43.4)	<0.001
	2=occasionally	140 (31.5)	61 (31.6)	79 (31.5)	
	3= very frequently	152 (34.2)	89 (46.1)	63 (25.1)	
Usefulness	1 = not useful,	143 (32.2)	23 (11.9)	120 (47.8)	<0.001
	2=useful	179 (40.3)	92 (47.7)	87 (34.7)	
	3=very useful	122 (27.5)	78 (40.4)	44 (17.5)	
Inputs for production					
Variety (If yes=1; otherwise 0)		273 (61.5)	137 (71.0)	136 (54.2)	<0.001
NPK (kg per ha)		90.7 (71.6)	89.4 (67.4)	91.7 (74.8)	0.734
Seed (kg per ha)		12.9 (9.7)	12.2 (8.2)	13.5 (10.7)	0.161
Human labour (person-days per ha)		66.4 (23.1)	69.5 (22.1)	64.1 (23.6)	0.014
Bullock labour (person-days per ha)		15.5 (7.8)	16.4 (6.2)	14.9 (8.8)	0.038
Farm machine (hours per ha)		14.9 (7.0)	15.9 (5.7)	14.1 (7.8)	0.008
FYM (tonnes per ha)		2.4 (4.0)	2.3 (3.9)	2.4 (4.1)	0.959

Notes #Benefits perception index is constructed using PCA of benefits of soil bunds perceived by the farmers for reduction in soil loss, run-off, and improving groundwater table, soil moisture, and fertility.

Table 2 Group-specific and meta-frontier technical efficiency under variable returns to scale (VRS)

Category	Technical efficiency	Mean	SD	Min	Max
Adopters	GSTE	0.83	0.16	0.39	1.00
	MFTE	0.68	0.16	0.35	0.94
	MTR	0.82	1.00	0.90	0.94
Non-adopters	GSTE	0.84	0.13	0.38	0.97
	MFTE	0.53	0.14	0.28	0.84
	MTR	0.63	1.08	0.74	0.87

Notes: GSTE is group-specific technical score; MFTE is meta-frontier technical score; MTR is meta-technology ratio.

Table 3 Distribution of group-specific and meta-frontier of technical efficiency scores (%)

TE class	Group-specific		Meta-frontier
	Adopters	Non-adopters	All farms
30–40	0.50	0.40	12.70
40–50	3.60	3.20	21.60
50–60	8.30	6.40	18.00
60–70	8.30	6.40	17.30
70–80	13.50	5.20	16.20
80–90	20.20	36.30	9.20
90–100	45.60	42.20	5.00
Total	193(100)	251(100)	444 (100)

The fertility of the soil in the study area is poor, and its carbon content is low (Wani 2011). Larger the number of livestock units, higher the amount of manure; and the application of manure favourably affects soil health and, in turn, the efficiency in sorghum production. The type of soil and the slope of the plot are found to have a negative influence on efficiency. Generally, higher the slope, higher the soil erosion—the top, fertile layer of soil is washed away, reducing the productive capacity and health of the soil (Sharda and Dogra 2013) and, in turn, its efficiency.

The infiltration capacity of black soils is very low in comparison to that of red soils, and the low infiltration capacity frequently leads to waterlogging and cracking and lowers productivity and, thereby, efficiency in sorghum production. The production capacity of fertile soils is greater than that of less fertile soils. Fertile soils conserve soil moisture and these are resilient to drought conditions. Soil fertility is negatively associated with inefficiency; interestingly, though, fertility has an insignificant effect on inefficiency in the plots of non-adopters, because the soil bunds on their plots conserve soil moisture despite the soil being fertile.

Training farmers had a negative effect on inefficiency. Training improves farmers' understanding of the adverse effects of soil erosion and of the benefits of adopting conservation measures and the improved package of practices. Our results are consistent with the findings of earlier studies (Tipi et al. 2009: Majumder et al. 2016).

Access to extension service centres had a positive effect on the efficiency of the plots of adopters and non-adopters. By visiting extension service centers, farmers learn of quality inputs (improved seeds, micronutrients, and fertilizers) and of the improved package of practices that helps improve efficiency. Visits to model watersheds to get real, field-level experience of the effectiveness of conservation measures, or exposure visits, had a favorable influence on efficiency for adopters. The influence on efficiency was insignificant for non-adopters (farmers of untreated areas) because they did not have the opportunity to make an exposure visit.

Impact of NRM technologies on technical inefficiency

The results of the falsification test (Table 5) show the validity of the taken instrumental variables. In the selection model, the 'perceived benefits of soil bunds on reducing the run-off' are significantly positive, as are the 'perceived benefits of soil bunds on enhancing soil moisture', but both variables are insignificant in the non-adopter outcome model, implying that these have no significant effect on efficiency. Therefore, it can be stated that the selected instruments are valid.

Among household-specific features, off-farm income, farm assets, and access to credit are associated

Table 4 Factors affecting group-specific technical inefficiency in sorghum cultivation

Variables	Adopters			Non-adopters		
	Estimates	confidence intervals (alpha 0.05)		Estimates	confidence intervals (alpha 0.05)	
Intercept	5.415**	3.049	11.842	–3.323	–9.318	1.510
Household-level characteristics						
Head	–1.087**	–2.850	–0.422	0.750**	0.070	1.783
Age	–0.087**	–0.173	–0.080	0.018	–0.006	0.052
Education	0.045	–0.039	0.155	0.064**	0.004	0.170
Dependency ratio	–3.402**	–6.682	–3.147	–1.582**	–3.140	–0.943
Livestock	–0.248**	–0.554	–0.153	0.090**	0.017	0.239
Farm asset index	–8.208**	–17.174	–3.494	4.670**	3.737	9.116
Access to credit	–3.280**	–6.385	–3.183	0.632	–0.141	1.633
Farm/plot-level characteristics						
Tenure	0.569	–0.305	1.772	0.419	–0.207	1.214
Plot size	0.030	–0.795	1.072	–0.254	–0.849	0.280
slope of plot	1.882**	1.618	3.875	1.083**	0.017	2.513
Red soil	0.513	–0.838	2.304	0.578	–0.409	1.767
Black soil	2.865**	2.393	5.760	1.513**	0.745	3.120
Soil erosion (high)	0.744	–0.304	2.221	–0.264	–1.134	0.370
Soil erosion (medium)	0.333	–1.088	1.972	0.852**	0.150	2.203
Fertility of plot (high)	–4.822**	–9.972	–4.485	1.787	–1.170	4.104
Fertility of plot (medium)	–2.806**	–6.587	–1.919	1.725	–1.274	4.047
Variety	1.187	0.780	2.713	0.069	–0.656	0.759
Perception of farmers						
Risk perception	0.088	–0.536	0.882	–0.369**	–0.955	–0.017
Benefit perception index	–0.703**	–1.504	–0.511	–0.424**	–0.841	–0.310
Extension and Training services						
Training	–2.071**	–4.205	–1.692	0.369	–0.369	1.199
Visits to KVK and RSK	–0.918**	–0.844	–1.788	–0.186**	–0.461	–0.048
Exposure visits	–0.469**	–0.166	–1.283	–0.020	–0.375	0.395
Regional Dummy						
Tumkur	–0.306	–1.606	0.814	–0.686**	–1.751	–0.111
Bidar	–1.501**	–3.551	–0.798	–0.889**	–2.054	–0.302
Gadag	–3.970**	–7.832	–3.607	–2.280**	–4.365	–1.595
Sigma	1.422	1.471	2.427	1.054	1.012	1.686

Note ** If the confidence interval (measured @5%) is devoid of zero, then the coefficient is significant at 5% level of significance.

Table 5 Falsification test for validity of selected instruments

Instrument variables	Selection model			Non-adopters outcome model		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Intercept	0.201	0.081	0.013	1.971	0.126	0.000
Perceived benefits of soil bunds on reducing the run-off	0.041	0.017	0.016	–0.015	0.026	0.546
Perceived benefits of soil bunds on enhancing soil moisture	0.033	0.020	0.094	0.031	0.031	0.330
$\chi^2(2)$	4.993		0.007	0.635		0.531
Observations (plots)	444			251		

positively with the adoption of NRM technologies (Table 6). Off-farm income may improve the financial capacity of resource-poor farmers and, thereby, the probability of adoption of NRM technologies (Ervin and Ervin 1982; Lapar and Pandey 1999) or, on the other hand, negatively affect adoption (Pender and Kerr 1998; Shiferaw and Holden 2000; Gebremedhin and Swinton 2003; Tenge, De Graaff, and Hella 2004; Amsalu and De Graaff 2007), as off-farm sources of income might reduce farmers' interest in farming and in investing in conservation measures (Ervin and Ervin, 1982; Bravo-Ureta et al. 2006; Teklewold and Köhlin 2011).

As NRM technologies are capital-intensive, and few farmers in the region have the capacity to invest, access to credit helps them overcome their credit constraints and positively affects adoption. Other researchers (Pattanayak et al. 2003) report similar findings.

The slope of a plot, level of erosion, and tenure have a significant and positive bearing on the take-up of conservation technologies. Slope is one of the important factors influencing soil erosion. Higher the slope, higher the soil loss due to water erosion. The slope of a plot also negatively influences the availability of soil moisture for crop growth. Numerous studies report a positive association of slope with the adoption of NRM technologies (Ervin and Ervin 1982; Shiferaw and Holden 1998; Bekele and Drake 2003; Gebremedhin and Swinton 2003; Amsalu and De Graaff 2007; Dessie, Wurzinger, and Hauser 2012).

The extent of soil erosion, or the loss of productive soil from the field, is another crucial factor determining adoption. Adoption is higher for farmers who perceive that soil erosion is affecting the productivity of their farm negatively (Norris and Batie 1987; Shiferaw and Holden 1998; Willy and Holm-Müller 2013).

The effects of the adoption of NRM technologies are less visible or tangible in the short term than in the long term, and farmers on short-term leases have less incentive to invest. Many studies report a positive relationship between tenure security and the adoption of NRM technologies (Shiferaw and Holden 1998; Teklewold and Köhlin 2011b), similar to our results. We also found that the fertility level negatively affects adoption.

The plots are relatively flat, and the soil depth is sufficient for good crop growth; the marginal benefits, or incremental yield changes, are very low, and farmers do not consider investing in such plots worthwhile. Our results are in line with other studies (Amsalu and De Graaff 2007; Tesfaye et al. 2014).

Training and extension services are associated with a higher likelihood of adoption of NRM technologies—which are knowledge-intensive (Barrett et al. 2002) and require appropriate structural design and location and stability and durability measures—and inadequate technical support is a major reason for low adoption (Bekele and Drake 2003; Dessie et al. 2012). Therefore, and in conformity with earlier studies (Sidibé 2005), proper training is positively associated with adoption of NRM technologies.

Access to extension services informs farmers about NRM technologies that are suitable and available, and of the technical know-how, and it helps farmers understand that soil erosion can potentially reduce production and that it has negative, long-term consequences. We found that visits to Krishi Vigyan Kendras and Raita Samparka Kendras are positively associated with adoption, as reported by many researchers (Mbaga-Semgalawe and Folmer 2000; Adegbola and Gardebroek 2007; Di Falco, Teklewold and Köhlin 2011; Veronesi, and Yesuf 2011; Mugonola et al. 2013; Mango et al. 2017). A high perception of risk is positively associated with adoption, as farmers who perceive that the risk of crop failure is high try to minimize their risk by adopting NRM technologies.

Farmers who interact with others about the benefits of conservation technologies rated such interactions highly useful and they were associated with a higher probability of adoption. Social networks positively influence the chances of the uptake of conservation measures, as expected. Community- or watershed-level efforts are needed to improve adoption; therefore, social networks are critical. Moreover, social networks encourage cooperative behaviour—a prerequisite for conservation programmes to succeed—since the flow of water from plots is interconnected. Our findings tie up well with earlier studies (Krishna 2001; Nyangena 2008; Teshome, Rolker, and de Graaff 2013)

Treatment effects

Counterfactual analysis shows that the ATT is –0.24, or soil bunds can reduce technical inefficiency in sorghum production for adopter farms by around

Table 6 Full information maximum likelihood estimates of endogenous switching regression model

	Selection		Adoption		Non-adoption	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	–3.785	1.197	0.824	0.466*	0.308	0.129
Household-specific features						
Head	0.491*	0.275	0.003	0.065	0.039	0.029
Age	–0.004	0.008	–0.001	0.002	–0.001	0.001
Education	–0.002	0.023	–0.011*	0.006	0.004	0.002
Dependency ratio	–0.354	0.237	–0.053	0.062	–0.001	0.023
Off'farm income	1.170***	0.215	–0.036**	0.100	–0.023*	0.029
Livestock	–0.003	0.036	0.010	0.010	–0.004*	0.004
Farm asset index	0.176*	0.054	0.274	0.200	0.025	0.093
Access to credit	0.071**	0.212	–0.016*	0.064	–0.070***	0.023
Plot-level features						
slope of plot	1.088***	0.233	0.242**	0.100	0.008*	0.027
Red soil	0.348	0.298	0.011	0.085	0.004	0.031
Black soil	0.234	0.292	0.035	0.082	0.015	0.029
Soil erosion (high)	0.117*	0.055	0.026	0.066	0.013*	0.027
Soil erosion (medium)	–0.380	0.304	0.103	0.082	–0.027	0.031
Fertility of plot (high)	–0.135	0.525	0.178	0.131	–0.022*	0.055
Fertility of plot (medium)	–0.353	0.528	0.179	0.134	0.014	0.053
Tenure	0.285**	0.031	0.007	0.066	–0.015*	0.024
Extension services						
Training	0.353*	0.120	–0.118*	0.068	–0.019	0.022
Visits to KVK and RSK	0.114*	0.061	–0.022	0.019	–0.002	0.007
Risk perception	0.296***	0.079	–0.024	0.021	–0.011	0.011
Social network						
Interaction with other farmers	0.311**	0.120	–0.003	0.039	–0.028*	0.015
Usefulness of interaction	0.636***	0.136	–0.004	0.050	–0.011	0.017
Inputs for production						
Variety	0.211	0.208	–0.105*	0.060	–0.033	0.022
NPK	–0.002	0.001	0.0001	0.004	0.001***	0.0002
SEED	–0.014	0.014	–0.004	0.004	–0.002	0.001
Human labour	0.005	0.005	0.003**	–0.001	0.014***	0.005
Bullock labour	–0.015	0.017	0.010**	–0.004	0.037***	0.002
Farm machine	–0.072***	0.016	0.001	–0.006	0.017***	0.002
FYM	–0.209***	0.050	0.050**	0.016	0.008	0.005
Regional Dummy						
Tukumkur	–0.311	0.275	–0.034	0.072	0.020	0.031
Bidar	–0.209	0.280	–0.014	0.072	–0.091***	0.030
Gadag	–0.362	0.289	–0.105	0.079	–0.014	0.030
Instrument variables@						
PBrunoff	0.067*	0.070				
PBmoisture	0.074	0.088				
sigma			0.160***	0.009	0.333***	0.017
rho			–0.536*	0.305	–0.074	0.445
Joint significance of plot-level characteristics df=15, stat= 29.099 0.01562 *						
Wald test: X2 = 147.1, df = 38, P(> X2) =0.000						

Note PBrunoff indicates the 'perceived benefits of soil bunds on reducing the run-off; PBmoisture indicated the 'perceived benefits of soil bunds on enhancing soil moisture'

Table 7 Treatment effects of natural resource management technology on adopter and non-adopter

Sub-sample	Decision		Treatment Effects	Change (%)
	Adopters	Non-adopters		
Adopters	1.56 (0.24)	1.80 (0.41)	ATT= –0.24*** (0.02)	–13.33
Non-adopters	1.61 (0.25)	2.02 (0.52)	ATU= –0.41*** (0.03)	–20.29
Heterogeneity effects	–0.056 (0.02)	–0.22 (0.04)	ATH= 0.17(0.03)	

Notes: Figures in parentheses are standard errors; *** indicates significance level at 1%.ATT is average treatment effect on treated (adopters)ATU is average treatment effect on untreated (non-adopters)ATH is average treatment heterogeneity

13.33% (Table 7). The ATU indicates that technical inefficiency can be reduced by 20.29% for non-adopter farms.

Conclusions

This study assesses the factors affecting the adoption of NRM technologies—i.e., soil bunds—which are highly recommended in the drought-prone areas of Karnataka. We used the double bootstrap DEA method to estimate the bias-corrected efficiency scores and the meta-frontier approach to compute the MTR. We used the ESR model to control for the heterogeneity effects of observed and unobserved factors.

We observed that the key factors affecting adoption are access to credit, extension services, and social networks; therefore, these factors need to be considered in formulating conservation programmes. We found that the TE of sorghum production may be enhanced by improving access to credit, the perception of the benefits of adopting NRM technologies, training, exposure visits, and extension services.

The observed MTR is 0.82 for adopters and 0.63 for non-adopters, or that shifting from non-adopters to adopters can improve the efficiency of sorghum production by 30%. The results of the ESR show that the ATT is “0.24, or that adopting soil bunds would reduce the inefficiency in sorghum production by around 13%.

Hence, we construe that the adoption of NRM technologies (soil bunds) could be an important strategy to enhance the performance of sorghum production in the drought-prone areas of the semi-arid tropics of India and, thereby, sustain the natural resources and livelihoods of resource-poor farmers.

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