ELSEVIER
www.elsevier.com/locate/worlddev

World Development Vol. 35, No. 8, pp. 1436–1449, 2007
© 2007 Elsevier Ltd. All rights reserved
0305-750X/$ - see front matter

doi:10.1016/j.worlddev.2007.04.006

Evaluating Social Impacts of Watershed Development in India

R.A. HOPE *
Oxford University Centre for the Environment (OUCE), UK

Summary. — Watershed development is an important policy instrument for rural development in many developing countries. However, evidence of the distribution and magnitude of social impacts attributable to watershed interventions is often ambiguous. This study uses a propensity score matching method to estimate social impacts on gross agricultural returns and domestic water collection times from treatment and control watershed data in the state of Madhya Pradesh, India. Results illustrate how matching methods can objectively estimate social impacts of watershed development across intended beneficiary groups. This promotes improved understanding of the performance of current watershed projects and provides inputs for the appropriate design of future rural development interventions.
© 2007 Elsevier Ltd. All rights reserved.

Key words — Asia, India, propensity score matching, rural development, watershed development

> *"The real area of focus has to be our unirrigated and dry land areas. Watershed development and rain water harvesting hold out immense promise in addressing this issue . . . I would like to make it perfectly clear that our vision of Indian agriculture continues and will continue to be based on smallholder farming."*

Dr. Manmohan Singh, Prime Minister of India, March 2005. [1]

> *"An estimated 27% of farmers did not like farming because it was not profitable.*
> *In all, 40% felt that, given a choice, they would take up some other career."*

National survey of farmers in rural India, July 2005. [2]

1. INTRODUCTION

Watershed development is an approach to raise agricultural productivity, conserve natural resources and reduce poverty in the world's semi-arid tropical regions, particularly sub-Saharan Africa and South Asia (Kerr, Pangare, & Pangare, 2002). These areas are commonly of low agricultural potential, suffer land degradation, and are often characterized by high levels of food insecurity and income poverty. A principal attraction of watershed development is that by capturing rainfall in the wet season, water may be available in drier periods offering several potential benefits—increasing soil moisture for rainfed agriculture, augmenting groundwater recharge for dry season irrigation, or drinking water supply, and capturing run-off for storage (e.g., ponds, tanks) for multiple productive or consumptive uses (Farrington, Turton, & James, 1999). However, emerging global evidence suggests that while watershed

* An earlier version of this paper benefited from the valuable insights of four anonymous referees. The Rajiv Gandhi Mission for Watershed Development (Bhopal) and the Rural Research Laboratory (Bhopal) provided data and support. Ashvin Gosain (IIT—Delhi) and Ian Calder (University of Newcastle) led the hydrological research in the study area, which contributed to the development of this study. Mamta Borgoyary and Sunandan Tiwari (Winrock International India) and Achraj Bhandari and Pradeep Lodha (IIT—Delhi) designed and administered the questionnaire. This publication is an output from a research project funded by the UK Department for International Development (DFID) for the benefit of developing countries. The views here are not necessarily those of DFID (R8171—Forestry Research Program).

development has delivered significant public benefits there are limits and trade-offs to modifying watersheds due to complex hydrological and social systems' interactions (Calder, 2005). For example, in the dryland areas of India watershed development has been associated with extreme social hardship due to changing spatial and seasonal patterns of surface water and groundwater access, which often hit the poorest hardest (Calder, 2005, pp. 139–140). As the two introductory quotes illustrate, while the political priority for watershed development remains high in India, the contribution of watershed development to the livelihoods of millions of poor rural farmers seems more uncertain.

Since the 1970s, India has invested significantly in watershed development as a driver of rural development (Joshi, Jha, Wani, Joshi, & Shiyani, 2005), partly in an attempt to scale up successes from a handful of well-known village-level watershed projects, such as Pani Panchayat, Ralegaon Siddhi and Sukhomajri (Turton, Warner, & Groom, 1998). While the focus of watershed development in India has modified over the last 20 years from soil conservation to water conservation to now include a more participatory planning approach, evaluation studies estimating the distribution or magnitude of social impacts from watershed development are often unclear or disputed (Kerr *et al*., 2002; World Bank, 2004). Given that in the region of US$500 million per year is allocated to watershed development in India, that there is a need to better understand the distribution of social impacts. Improved knowledge will help determine how watershed projects affect intended beneficiaries in order to evaluate the performance of current watershed projects and to aid the appropriate design of future projects (Farrington *et al*., 1999; Kerr *et al*., 2002; World Bank, 2004).

Social benefits commonly associated with watershed development include improved agricultural yields and farmer returns, increased access to domestic water and new employment opportunities. However, these benefits will vary for different resource user groups located across most watersheds. This is partly due to watershed development interventions modifying land use impacts on water resources, which may increase upstream water availability while modifying downstream water access (Batchelor, Rao, & James, 2000; Calder, 2005; Gosain *et al*., 2006). How such changes impact on resource user groups, who may compete for water for agriculture or domestic use, will remain ambiguous while uncertainty surrounds how benefits are distributed amongst different user groups.

Estimating social impacts of a watershed project requires measurement of defined social outcome indicators conditional on the same indicators in the absence of a project. This type of analysis is rare (Kerr *et al*., 2002). Identifying and measuring causal linkages of project impacts on poverty is challenged by disentangling project impacts from non-project influences such as employment trends, crop price shifts, climatic variability, or new legislation. In theory, the impact for a household in a treated watershed is the difference between an outcome indicator measured with the project and without it. Treated watershed data can be collected in a reasonably straightforward manner once outcome indicators have been agreed, targets set and monitoring systems put in place. Non-treatment data are more problematic as the data are effectively "unobserved" since an individual or household cannot be both a participant and a non-participant. While control watershed populations are commonly monitored, a significant methodological constraint is matching a treated household with a non-treated household due to economic, social or agro-climatic differences. One approach that attempts to overcome such problems is propensity score matching (Baker, 2000; Deininger, Hoogeveen, & Kinsey, 2004; Heckman, Ichimura, & Todd, 1997, 1998; Jalan & Ravallion, 1999, 2003; Rosenbaum & Rubin, 1985).

The purpose of this paper is to illustrate a matching method based on the application of household data from microwatersheds in rural Madhya Pradesh, and to consider its wider replicability. Three outcome indicators are derived from the available data: (a) gross returns to kharif agriculture (monsoon crop); (b) gross returns to rabi agriculture (post-monsoon crop); and, (c) domestic water collection time in the dry season (March through July). The analysis estimates who benefits from watershed development, and by how much, by purposively comparing private (economic) returns from a land-based intervention alongside changes in public access to drinking water. The rest of the paper is structured as follows: Section 2 explains the problem of bias in evaluating impact estimates and how matching methods can reduce bias. Section 3 discusses the research context, data, and study limitations. Results are presented in Section 4 and Section 5 concludes with wider implications.

2. EVALUATING SOCIAL IMPACTS OF WATERSHED DEVELOPMENT

Criticisms of watershed development projects mainly benefiting people with land have resulted in a more inclusive "watershed plus" approach. This attempts to broaden social benefits from improved agricultural yields or increased agricultural returns to include improved access to drinking water, empowerment and non-land-based employment opportunities (DANIDA, 2004). However, constructing impact indicators that correspond to such goals, and which can be directly linked to interventions, is often not straightforward. The need to establish measurable indicators directly linked to planned interventions is a key step in social impact evaluation (Baker, 2000). Here, gross agricultural returns and domestic water collection times are evaluated based on available data to estimate land and non-land-based impacts.

(a) *The problem*

Measuring changes in agricultural returns (or time collecting domestic water) requires a method to estimate unbiased project impacts. This promotes assessment of a counter-factual, that is, what would have occurred if the project had not taken place. Two methods drawn from the impact evaluation literature are reviewed by Jalan and Ravallion (1999). First, reflexive comparisons collect baseline data on probable participants before a project is implemented, say in the next raft of watersheds for treatment. These data are compared to the same individuals after project implementation. This method is followed in many watershed programs across India though a review by Kerr *et al.* (2002) in Andhra Pradesh and Maharashtra found significant data problems or lack of data records. This method could be extended to include observations on non-participants, before and after the intervention, allowing "double-difference" estimates of project impacts. Second, in cases where it is unfeasible or unethical to set up a pre-intervention sample, such as in food aid or educational programs, a control group can be set up by matching project participants to non-participants from a wider survey, such as a national census. Propensity score matching methods are applied on the basis of similarities between observed characteristics in both samples (Heckman *et al.*, 1997, Heckman, Ichimura, & Todd, 1998; Rosenbaum & Rubin, 1985).

Problems arise in both methods. Reflexive and double-difference comparisons are challenged by attrition, where a non-random subset of the baseline sample drops out for various reasons. Pre-project randomization may not be feasible and there is also the problem of selective non-participation among those randomly chosen for the project. Matching methods can avoid these problems but create a different set of challenges. Four features are important in matching:

- Participants and controls have the same distribution of unobserved characteristics.
- Participants and controls share the same distribution of observed characteristics.
- The same questionnaire is administered to both groups.
- Participants and control share a comparable social, economic or agro-climatic environment that will not unduly influence project impacts across samples.

Jalan and Ravallion (1999) note that in the absence of these features simple difference measures between participants and matched non-participants will result in a biased estimate of the project impact. An empirical example that compared bias from observed and unobserved characteristics indicated that biases in naïve estimates were huge but careful matching of the comparison group based on observables greatly reduced the bias (Heckman, Ichimura, Smith, & Todd, 1998).

(b) *Propensity score matching methods*

Given data on potential beneficiaries in a watershed development project and a random sample drawn from a comparable watershed with similar social, infrastructure, agro-climatic, and economic characteristics, participants in the treatment watershed can be matched with non-participants in a control watershed. Survey data must include information that helps predict participation in the program, here having access to land (e.g., socio-economic characteristics) and a threshold level for domestic water collection (above or below x minutes per day).

The aim is to match a participant with a non-participant using the entire dimension of a vector of variables (X), that is, a match occurs where two individuals from each sample record an identical match. This is likely to be rare and generally impractical (Jalan & Ravallion, 1999). Rosenbaum and Rubin (1983) show that matching can be performed conditioning on

$P(X)$ alone rather than on X, where $P(X) = \text{Prob}(D = 1/X)$ is the probability of participating conditional on X, the propensity score of X. Jalan and Ravallion note that "if outcomes without the intervention are independent of participation given X then they are also independent of participation given $P(X)$." This reduces a multi-dimensional matching problem to a single-dimensional problem.

A logistic regression model can be used to calculate a propensity score for each observation in the treatment and non-treatment watershed samples. When there is over-sampling of participants (as here), choice-based sampling methods can be used to weight the observations (Manski & Lerman, 1977). This is not feasible here as the sampling weights are not known. However, matching can be based on the odds ratio $p_i = P_i(1 - P_i)$ where P_i is the estimated probability of participation for individual i. Using propensity scores, matched pairs are estimated across the two samples. [3] Using the estimated propensity scores, matched pairs are constructed on how close the scores are across the two samples. The nearest neighbor to the ith participant is defined as the non-participant that minimizes $\{p(x_i - x_j)\}^2$ over all j in the set of non-participants. Here, matches were only accepted for propensity scores with a difference less than 0.01. Heckman *et al.* (1997, 1998) find that failure to compare participants and controls at common values of matching variables is the single most important source of bias. A kernel density estimation procedure across a range of 100 scores was estimated using NLOGIT software (Greene, 2002) to ensure that matching only occurred over common values of propensity scores (Figure 1).

The mean impact of the watershed development on agricultural income is given by

$$I = \sum_{j=1}^{P} \left(Y_{j1} - \sum_{i=1}^{NP} Y_{ij0} \right) \Big/ P, \qquad (1)$$

where Y_{j1} is the post-intervention agricultural return of household j, Y_{ij0} is the agricultural return of the ith non-participant matched to the jth participant, P is the total number of participants and NP the total number of non-participants. The matching estimator used here is a "nearest neighbor" estimator where the closed non-participant is matched for each participant. [4] The impact estimation is the simple mean over the income or time difference between the participant and its matched non-participant.

(c) *Bias due to unobservables*

The matching estimate described above may be biased even if comparison groups are carefully selected. Another source of bias arises when there is a systematic relationship between, say, watershed participation and outcomes in the absence of the program. This is problematic if there are unobserved variables that jointly influence outcomes and watershed participation conditional on the observed variables in the data. One approach to test for bias is to test for partial correlation between income and the residuals in the participation model (Jalan & Ravallion, 1999). A regression is run on a combined sample of treated and control households with land as the dependent variable and independent variables including the propensity scores, the residuals from the participation

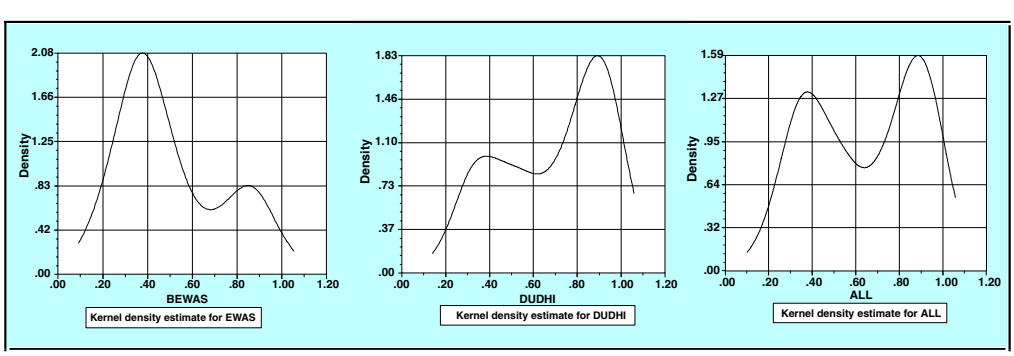

Figure 1. *Kernel density estimation for land propensity scores.*

model and control variables from the participation model (Deininger *et al.*, 2004). Selection bias is indicated if we can reject the null hypothesis that the coefficient for the residuals is significantly different from zero. Identification requires at least one variable in the linear regression to be excluded that is in the participation model. Given the nature of watershed selection, location clearly matters to participation for agricultural gains. A plausible exclusion restriction suggests removing the variable for location (watershed as a dummy variable) in testing for unobservables. It is assumed that location of households does not matter to income independently of participation. While an instrumental variables' estimator identifies the causal effect to unobserved heterogeneity, the validity of the exclusion restriction may be questionable with single cross-sectional data (Jalan & Ravallion, 2003). The validity of testing for bias to domestic water benefits from unobservables seems less applicable due to the almost universal nature of water collection in both watersheds and the public goods nature of interventions to improve drinking water access. Given these considerations, only bias to agricultural returns from unobservables is tested.

3. WATERSHED DEVELOPMENT IN MADHYA PRADESH

After India experienced steady agricultural growth of 4.8% (1992–97), the rate has dipped to 1.8% (1997–2002) with worrying implications for rural development and poverty reduction (World Bank, 2003). Madhya Pradesh (MP) is the second largest state in India and one of the poorest states with the majority of the poor living in rural areas and depending on agriculture (DFID, 2004). NSSO (2005) estimate that 67% of rural households in MP engage in farming activities compared to an all-India average of 60%. Poverty rates in MP are estimated to have fallen in the period 1993–94 (43%) to 1999–2000 (37%) with agricultural growth appearing to be one of the key drivers of reducing poverty (DFID, 2004; WaterAid, 2005). Improving agricultural yields and returns in key crops such as paddy (monsoon crop or "kharif") and wheat (post-monsoon season or "rabi") appears feasible given that current yields are roughly half of national averages (GoI, 2003).

A related challenge for watershed development concerns unintended impacts that increasing water use by agriculture from surface water and groundwater sources throughout the year have on domestic water availability in summer months (WaterAid, 2005), particularly for poor and vulnerable groups, such as Scheduled Castes and Scheduled Tribes (SC/ST) (DFID, 2004). These challenges inform some of the objectives of the state-level Rajiv Gandhi Mission for Watershed Development (RGWDM) programs, which consolidated all watershed programs in 1994 and has since treated over 1.4 million hectares of land in 7,600 villages by 2006. [5] Microwatersheds, measuring between 500 and 1,000 hectares, represent the common implementation unit in MP and across India (Turton *et al.*, 1998). One microwatershed treated during 1997–2000 is the Dudhi microwatershed in Raisen District in central MP. It neighbors the untreated Bewas microwatershed, which is chosen as the control group to illustrate the matching method (Figure 2).

(a) *Study site*

The Dudhi and Bewas watersheds measure 600 and 750 hectares, respectively. Rainfall and potential evapotranspiration are estimated to be 1,196 mm per year and 1,486 mm per year, respectively, for measurements during the period 1994–2002 (Gosain *et al.*, 2006). [6] Surface run-off is lower in the Dudhi (263 mm per year) than the Bewas (416 mm per year). Soils vary from entisols in higher areas to inceptisols in lower areas within an altitudinal range of 600–700 m above sea level range (ibid). Agriculture is the main land use in both microwatersheds with approximately 10% forest cover in the Dudhi.

Selection of the Dudhi for watershed treatment involved collaboration between local government officials and the Rural Research Laboratory—Bhopal (RRL), which is a project implementing agency for the RGMWD. [7] Selection criteria for watershed treatment included water scarcity, [8] a low level of development influenced by remoteness, high unemployment and a high proportion of SC/ST. A particular problem identified for the Dudhi population was shortage of domestic water in summer months due to public wells drying (R. Ram, personal communication, 2005). The Dudhi has an estimated population of some 5,000 people and records significant variation in levels of illiteracy and employment

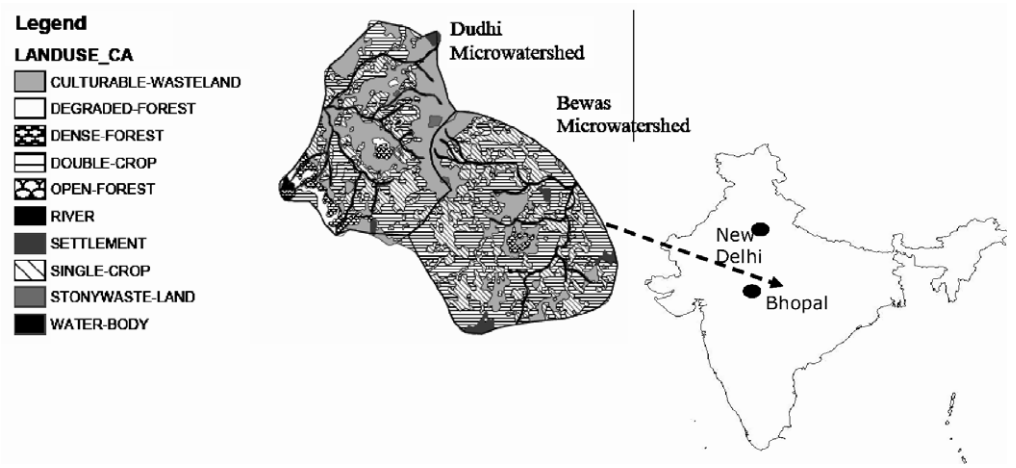

Figure 2. *Watershed location and land use. Adapted from Gosain et al. (2006).*

and SC/ST inhabitants in each of the eleven villages (Table 1). The Bewas has a smaller population of some 3,000 people across three villages and a similar variation in socio-economic indicators. Agriculture is a significant livelihood activity in both watersheds.

RRL provided own-project data on activities conducted in the Dudhi watershed for infrastructure, employment generation and a post-project assessment of changes in kharif and rabi yields. [9] Responding to domestic water problems, a significant financial investment was made in pond construction accounting for US$81,732. [10] of infrastructure spent. This was followed by an allocation of US$28,086 on trenches and US$13,464 on tree planting. On average, some 300 gulley plugs or boulder checks were constructed in each treatment village. In terms of the distribution of land investments, 94% of public land was treated compared to 73% of private land, though aggregate totals show that private land represented 68% of the total treated area compared to 32% for public land. Improvement in domestic water access is inferred by a reduction of dry wells in the summer months from 151 to 131.

RRL data report that 29% more rabi land and 19% more kharif land were farmed following watershed interventions. Impacts on average seasonal yields are estimated to be 84% higher (2 quintals [11] per ha) for kharif crops and 60% higher (3 quintals per ha) for rabi crops. Watershed employment opportunities were targeted to SC/ST and women groups, who received a 48% and 27% share of labor investment costs, respectively. Total employments days is estimated to be 170,000 person days, based on a standard rate of Rs 40 per day. Total watershed development expenditure is recorded to be greater than US$260,000 (R1.3 crore).

(b) *Data collection*

In 2004, a post-evaluation survey was administered concurrently in the Dudhi and Bewas microwatersheds on which the following analysis is based. [12] The survey captured information related to agricultural and domestic water access following watershed activities. The questionnaire was administered in the pre-monsoon months of 2004. A team of local enumerators collected data from a total of 580 households in the Dudhi watershed and 226 households in the Bewas watershed. This is roughly equivalent to a 50% sample of the total household population in both watersheds. A universal sampling strategy attempted to interview all available households on the days that the enumerators visited particular villages; no attempt was made to return to interview unavailable households. Enumerators were recruited locally and the questionnaire was administered in Hindi. The questionnaire included qualitative questions on the social impacts of watershed interventions.

Table 1. *Study villages*

Village	Households	SC/ST (%)	Illiteracy (%)		Agriculture (%)	
			Female	Male	Cultivators[a]	Laborers
Dudhi treatment watershed						
Amouli	38	78	48.7	18.7	43	53
Bichhuwa Jagir	92	41	26.6	9.3	39	51
Dabri	77	87	31.8	15.1	33	19
Dhilwar	127	26	13.3	7.1	37	59
Gorkha	87	77	15.1	9.3	25	53
Khiriya Ta Papda	21	43	20.5	11.5	75	25
Padariya Khurd	36	13	23.9	16.9	45	55
Padariya Rajadhar	133	37	25.6	9.2	42	29
Pipaliya Kalan	131	39	28.9	7.7	31	57
Suneti	157	66	18.5	9.5	36	37
Tekapar Khurd	116	39	20.0	7.8	63	31
Bewas non-treatment watershed						
Deokani	53	89	21.9	5.4	52	39
Imaliya	54	26	33.0	5.9	41	56
Searmau	443	46	17.2	8.2	15	37

SC/ST—scheduled caste/scheduled tribe.
Source: Government of India 2001 census.
[a] Distinction implies "cultivators" farm own land while "laborers" are paid workers.

(c) *Study limitations*

Data captured permits estimation of impacts of crop returns and domestic water collection times.[13] However, this is somewhat opportunistic as the survey designers did not plan to use a matching method. This results in data attrition, specifically for the sample of rabi farmers. As the kernel density figure illustrates, land distribution is skewed toward households in the Dudhi treatment watershed. Many households did not report land (see Table 2) and thus automatically dropped out of the sample for land return impact evaluation, though they were relevant for drinking water access impacts. While there is a sufficient control sample of non-treatment kharif farmers ($n = 77$) to match with the treatment sample ($n = 373$), there are limited available matches in the control sample of rabi farmers ($n = 18$) for the treatment group ($n = 87$). While data cleaning and a high matching tolerance limit (<0.01 propensity score difference) inevitably causes data attrition, this could have been improved by more effective data collection and management. This limits the implications of intervention impacts on rabi crop returns while providing a salutary lesson of the importance in early and integrated evaluation planning.

4. RESULTS

(a) *Descriptive data*

Descriptive data of the treatment and control watersheds are presented in Table 2. Households in the treatment watershed report an average annual income of US$267, of which 42% is derived from farm activities. This is reflected by a higher proportion of households with agricultural land in the Dudhi watershed (67%) than the Bewas (37%), though of households reporting farm land, kharif and rabi area farmed is comparable. Ownership of bullocks and buffaloes is higher in the Dudhi watershed where farming is more economically important. All households gain the majority of annual income from non-farm sources with migrant wage income representing roughly one third of this income. SC/ST groups represent just over one half of the social composition of each watershed, which is higher than the state average (WaterAid, 2005). Domestic water access is poor in both watersheds with a seasonal break-down illustrating that households on average spend around 90 minutes collecting water on a daily basis in the drier months of March through July. These data support the selection of the Dudhi watershed for watershed development on low income, agricultural

Table 2. *Descriptive data*

		Dudhi (treatment, $n = 580$)	Bewas (non-treatment, $n = 226$)
Total household income[a]		244.66	256.66
		(8.42)	(23.68)
Farm income		103.64	64.40
		(7.19)	(15.60)
Off-farm income	All sources	141.02	192.26
		(6.06)	(21.37)
	Migrant wage	51.08	62.20
		(3.71)	(12.31)
Scheduled caste/scheduled tribe		54%	55%
		(0.02)	(0.06)
Land[b] (acres)	Rainfed	5.25	5.21
		(0.20)	(0.79)
	Irrigated	3.87	3.17
		(0.39)	(1.02)
Daily domestic water collection (minutes per day)	March–July	85	94
		(3.57)	(11.46)
	August–October	47	48
		(1.98)	(5.41)
	November–February	46	45
		(1.80)	(5.29)
Bullocks (head)		1.13	0.67
		(0.06)	(0.13)
Buffaloes (head)		0.46	0.22
		(0.05)	(0.08)

Mean (standard error). Data are population-weighted averages. Income data are estimated from US$1 = Rs 50 (2004).
[a] Income outliers (>Rs 40,000 per year) are excluded.
[b] Figures reported only from households with land farmed, extreme values of >15 acres excluded, rainfed sample (Dudhi = 373, Bewas = 77), irrigated sample (Dudhi = 87, Bewas = 18).

dependency, poor domestic water access and a high population of SC/ST households.

Perceptions of the impact of watershed interventions amongst the treated Dudhi are presented in Table 3. Responses center on labor and water impacts. Coding identified five broad categories that reflect informant clusters of responses: (1) wage labor; (2) more water (generally); (3) water for livestock; (4) water for crops; and (5) no benefit. Wage labor opportunities associated with village-level activities were the most important impact reported (52%). The second highest response indicated that the activities had "no benefit" (23%). A cluster of water-related impacts were decomposed into benefits from "more water" (13%), "water for livestock" (9%), and "water for crops" (3%). In total, water-related benefits due to watershed activities account for one quarter of informant responses.

Table 3. *Qualitative evaluation of impacts*

	Frequency	Percent
Wage labor	464	52
No benefit	202	23
More water	117	13
Water for livestock	79	9
Water for crops	26	3
Total	888	100

Note: Respondents could identify up to two impacts.

(b) *Matching estimates*

Logistic regression model results are presented in Tables 4 and 6. Predictions for land

Table 4. *Logit model for land ownership*

	Coefficient (*B*)	Standard error	Significance	Exp(*B*)
WATERSHED	1.118	0.337	0.00**	3.058
BULLOCK	0.755	0.110	0.00**	2.128
BUFFALO	0.543	0.226	0.016*	1.721
SCST	−0.759	0.223	0.001**	0.468
HHINC	0.000	0.00	0.000**	1.000
CONSTANT	−0.913	0.381	0.017*	0.401

Variables: WATERSHED—Dudhi (dummy); BULLOCK—number of head, BUFFALO—number of head, SCST—scheduled caste/tribe; HHINC—annual household income.
Nagelkerke $R^2 = 0.316$; Hosmer and Lemeshow test ($X^2 = 13.74$; df = 8; $p > 0.05$).
* Significant at the 5% level.
** Significant at the 1% level.

ownership fit well with the descriptive data. As expected, living in the Dudhi increases the probability of owning land. Bullock ownership increases the probability of owning land while belonging to SC/ST household reduces the likelihood of land. Probability of land ownership is not influenced by annual income in the model. Other available variables were tested but did not improve the model fit as specified. Further, the model is tested for bias from unobservables. For identification, the location variable (watershed dummy) is excluded from the set of controls in the income regression (Table 5). The coefficient on the residuals from the participation regression was not significantly different from zero ($t = -0.42$). This indicates that selection bias on unobservables should not bias the matching estimates for crop returns.

Prior to matching, the estimated propensity scores for land ownership in the treated and non-treated watersheds were, respectively, 0.784 (standard error 0.009) and 0.519 (standard error 0.048). From the original sample, there are 361 households in the treatment watershed reporting kharif land ownership, of which 84 are evaluated after excluding missing or extreme value data and finding a sufficiently close match in the non-treatment sample. After matching there was a difference of 0.004 in the propensity scores of the two groups (0.644 for the treated group with a standard error of 0.021, and 0.648 for the non-treated group with a standard error of 0.021). Similarly, the matching process for the impact on rabi income resulted in the same pre-matching propensity scores (same logit model), which were reduced on matching to a difference of 0.004 between the treated group of rabi farmers (mean of 0.479 and standard error of 0.128) matched and the non-treatment propensity scores (mean of 0.483 and standard error of 0.130).

Table 5. *Selection bias results*

	Coefficient	*t*-Statistic
Constant	−17,286.02	−8.03
Scheduled caste/scheduled tribe	4,557.45	4.81
Bullock	−3,297.55	−6.07
Buffalo	351.04	0.83
Propensity score	33,964.24	10.48
Residuals	−410.33	−0.42

The logistic regression model for water collection was specified by households spending more than two hours per day collecting water in the dry months of March through July. Results indicate that belonging to an SC/ST is likely to more than double the probability of spending more than two hours collecting domestic water. Owning a buffalo is also a positive predictor (>1) of poor domestic water access. Alternatively, dummy variables for growing kharif or rabi crops or owning bullocks reduce the likelihood of spending more than two hours collecting water. Irrigating farmers are three times less likely than rainfed farmers to spend over two hours collecting water, which appears plausible. Water collection propensity scores for each watershed were, respectively, 0.355 (standard error 0.008) for the Dudhi and 0.401 (standard error 0.011) for the Bewas. After matching, there was an equal score of 0.351 (standard error 0.008) for both watershed groups at three decimal places.

Estimated average income impacts for kharif and rabi crops are presented in Table 7. After matching, results are stratified by social, income and land groups from the effective sample. The nearest neighbor estimate of the

Table 6. *Logit model for water collection*

	Coefficient (*B*)	Standard error	Significance	Exp(*B*)
SCST	0.89	0.25	0.00**	2.42
IRRIRABI (dummy)	−1.53	0.26	0.00**	0.22
RFDPADY (dummy)	−0.42	0.21	0.04**	0.66
BULLOCK	−0.15	0.08	0.06*	0.86
BUFFALO	0.25	0.09	0.01**	1.29
Constant	−0.76	0.24	0.00**	0.47

Variables: SCST—scheduled tribe/scheduled caste; IRRIRABI—irrigated a Rabi crop: RFDPADY—grow rainfed paddy; BULLOCK—no. of bullocks owned; BUFFALO—no. of buffaloes owned.
Naglekerke coefficient = 0.20; Hosmer and Lemeshow test ($X^2 = 7.06$; df = 6; $p > 0.05$).
* Significant at the 10% level.
** Significant at 1% and 5% level.

Table 7. *Crop income impacts (US$)*

		Kharif crop	Rabi crop
Full matched sample		−10.74	−25.03
		(7.36)	(15.37)
Social	SC/ST	−5.40	−61.12**
		(11.04)	(20.91)
	Other	−15.59	35.11*
		(9.90)	(12.57)
Income quartiles	Bottom	−11.00	−35.33
		(9.12)	(18.97)
	2nd quartile	−25.27	−22.54
		(11.51)	(31.40)
	3rd quartile	−24.09	−41.17
		(11.22)	(33.99)
	Top	20.20	−1.08
		(22.89)	(38.07)
Land quartiles	Bottom	−15.33	−46.68
		(10.55)	(26.79)
	2nd quartile	−17.77	−77.75*
		(9.34)	(23.49)
	3rd quartile	4.80	−23.08
		(11.18)	(25.77)
	Top	−13.00	66.20*
		(24.76)	(3.69)

Mean (standard error). Based on nearest neighbor propensity score estimation. Sample filter criteria: (a) Treatment kharif income is positive; (b) matched scores are accepted within a range of 0.01 points; (c) treatment households own land; (d) household income extreme values (>Rs 40,000 pa) excluded; (e) income change extreme values (>20,000) excluded; (f) quartile distribution estimated from matched landowners only.
* Indicates significance from the matched sample mean at the 5% level or lower.
** Indicates significance between 5% and 10%.

average impact across the sample is a loss of US$11 for a kharif crop and a loss of US$25 for a rabi crop. Stratification of kharif farmers indicates that SC/ST households fare better than other social groups though still record a loss of US$5. Income stratification reveals no significant difference from the group mean though the poorest quintile reports a loss (US$10) of approximately half of the second and third quintiles. The top income quintile reports the only income gain (US$20). Exploring kharif estimates by land quartiles reveals no clear pattern with no group with an estimate significantly different from the sample mean.

Table 8. *Domestic water collection impacts (minutes per day)*

		Water collection time[a]
Full matched sample ($n = 470$)		17.37 (2.46)
Social	SC/ST	18.32 (3.02)
	Other	16.19 (4.04)
Income quartiles	Bottom	12.83 (4.50)
	2nd quartile	17.14 (4.54)
	3rd quartile	8.57** (5.09)
	Top	31.03* (5.28)
Water collection quartiles (March–July)	Lowest time	62.65* (5.37)
	2nd quartile	35.36* (4.40)
	3rd quartile	15.57 (3.31)
	Highest time	−31.13* (3.16)

[a] Positive values indicate increased collection times in March–July period, negative values indicate a reduction. Based on nearest neighbor propensity score estimation. Sample filter criteria: (a) matched scores are accepted within a range of 0.01 points; (b) extreme values (>180 minutes per day) are excluded; (c) quartile distributions estimated from matched sample only.
* Indicates significance from the matched sample mean at the 5% level or lower.
** Indicates significance between 5% and 10%.

The third quartile has an estimated small positive value (US$5) with the other three quartiles falling in the range of a loss of US$13–18, which is not significantly different from the sample mean.

Rabi income impacts result in a significant loss (US$61) for the SC/ST households with other social groups recording a significant gain (US$35). Stratification by income indicates no significant difference between groups with the three bottom quartiles reporting losses greater than US$22 and the top quartile just failing to break-even. Land stratification reveals losses for the bottom three quartiles with a significant loss (US$78) for the second quartile which is mirrored by a significant gain for the top land quartile (US$66).

Domestic water collection impacts in the dry months are reported in Table 8. After matching, results are stratified by social and income groups and the existing water collection distribution for March through July. The mean impact is an increase of 17 min per day in the dry months. This impact is felt evenly by both social groups. Income stratification indicates a significant difference for the third quartile of 9 more minutes per day and 31 more minutes per day for the top income quartile. Estimates for the bottom two income quartiles indicate increased collection times of between 12 and 18 minutes per day. Finally, evaluating impacts against the existing distribution of water collection reveals that the interventions have most benefited those households who previously recorded the longest collection times leading to a reduction of 31 minutes per day. This positive finding is balanced by significant increases in collection times for the two groups with the lowest collection times, which are estimated to spend one hour more in (lowest quartile) or 30 minutes more in (second lowest quartile) collecting domestic water.

5. CONCLUSION

Watershed development remains a popular policy instrument for rural development in semi-arid areas of many developing countries. While much has been achieved in reducing rural poverty in recent years, it is uncertain how watershed development specifically contributes to development goals. Improved evaluation of watershed projects is necessary to provide information on what works (good design), for whom (beneficiary impact) and how (resource efficiency). This analysis has illustrated the steps in applying a propensity score matching method to estimate social impacts in one microwatershed in rural Madhya Pradesh, India. The study suggests that matching methods are suitable for watershed evaluation though wider implications of these results are constrained by the limited scale of the inquiry.

Findings indicate that the majority of farmers planting kharif crops are no better off after

the project in income terms with no significant variation amongst social, income or land stratified groups. The smaller group of rabi farmers fare even worse, on average, but significant variation is found across social groups and land ownership. This is partly explained by data attrition in matching and the results for rabi income impacts must be interpreted with caution. However, the general lack of improvement in agricultural returns does not correspond well with own-project evaluations of an 84% increase in kharif yield and a 60% increase in rabi yield. While these data are not necessarily comparable, this evaluation would, as a minimum, question if reported large yield increases have been maintained. Qualitative perceptions of project impacts suggest that impacts were short-term and mainly associated with project wage labor; longer term improvements in water access are not identified. This raises the issue of the timing of an impact evaluation and the need for projects to determine criteria for the duration and conditions for sustained impacts.

A positive social impact is estimated by a significant reduction in domestic water collection times for households with the highest collection times. While this is to be welcomed, these households still face considerable collection costs (e.g., physical, opportunity, health) and remain excluded from a basic level of domestic water access. [14] It is plausible that the estimated lower level of domestic water access may be related to new upstream water conservation structures capturing more water, as planned, without fully understanding downstream water implications (Batchelor *et al.*, 2000; Calder, 2005; World Bank, 2004). Understanding such perverse outcomes is beyond the scope of this study but underlines the need for impact evaluation to integrate social and biophysical studies.

Matching methods represent a useful approach for evaluating watershed development impacts subject to policy support and management priority. This study underlines that evaluation should be an early and integral component of a program in order to fulfill the following requirements: (a) careful estimation of a counter-factual group to establish statistical inferences with minimal attrition, (b) construction of measurable impact/outcome indicators that can be directly linked to watershed activities, and which respond to beneficiaries' priorities, (c) capacity to design, implement, process, analyze and store social (and biophysical) data, (d) test project design and triangulate findings through qualitative inquiry, (e) determine timing of an evaluation and conditions for sustained impacts, and (f) effective dissemination and uptake of results (Baker, 2000). Though reducing the ambiguity of watershed development impacts may not be in the interests of all, if the "immense promise" of watershed development is to be realized, as Manmohan Singh hopes in India, knowing what works, for whom and by how much, would seem to be essential information.

NOTES

1. Full interview available at: http://www.ifpri.org/pubs/newsletters/ifpriforum/200503/if10Singh.htm.

2. Based on a sample of 51,770 farmer households across 6,638 rural villages (NSSO, 2005).

3. Command syntax for this process in SPSS is available at: http://pages.infinit.net/rlevesque/index.htm.

4. Nearest five neighbors or a kernel-weighted estimation may reduce scores (Jalan & Ravallion, 1999) though Rubin and Thomas (2000) find no pattern in bias between a nearest neighbor or nearest five neighbors.

5. Data accessed May 2006, available at: http://www.mp.nic.in/rgm/watershed.htm.

6. The hydrological analysis was part of the DFID-funded Low flows project (R8174).

7. The RGMWD consolidated existing watershed programs in MP in 1994 to provide impetus and focus to overlapping state-level and national-level initiatives. This included national programs such as the Drought Prone Area Program (DPAP), Integrated Watershed Development Program (IWDP) and National Watershed Development Project for Rainfed Areas (NWDPRA) plus state-level Department of Rural Development and Department of Agriculture projects.

8. While mean annual rainfall is estimated at over 1,000 mm per year, the area is considered to be drought prone due to high levels of annual variability. The Central Water Commission (Delhi) defines drought

prone areas where (a) annual rainfall is less than 75% of the average one in five years and (b) less than 30% of cultivated area is irrigated (WaterAid, 2005).

9. Data tables available from the author.

10. All data reported at US$1 = Rs 50.

11. 1 quintal = 100 kg.

12. It is noted that the survey designers did not plan to use matching methods though they collected control data. This partly explains some of the later analytical difficulties and highlights the need to plan impact evaluation from an early stage and in an integrated manner.

13. Specification of agricultural yield as an indicator of land treatment is considered a more accurate social impact measure than change in agricultural income as this permits a grasp of food security benefits from non-marketed crops. These data were not collected.

14. This finding is not biased by rainfall variability or drought events as the matching method isolates such impacts through careful selection of a control watershed.

REFERENCES

Baker, J. L. (2000). *Evaluating the impact of development projects on poverty. A handbook for practitioners*. Washington, DC: World Bank.

Batchelor, C. H., Rao, M. S., & James, A. J. (2000) Karnataka Watershed Development Project: Water Resources Audit. KAWAD report no. 17. Bangalore: KAWAD Society.

Calder, I. R. (2005). *Blue revolution: Integrated land and water resource management* (2nd ed.). London: Earthscan.

DANIDA (2004). Case studies and lessons learnt—Karnataka Watershed Development Project. DANIDA Watershed Development Programme. New Delhi: DANIDA.

Deininger, K., Hoogeveen, H., & Kinsey, B. H. (2004). Economic benefits and costs of land redistribution in Zimbabwe in the early 1980s. *World Development, 32*(10), 1697–1709.

DFID (2004). India Country Plan. Partnership for Development. New Delhi: DFID.

Farrington, J., Turton, C., & James, A. J. (1999). *Participatory watershed development: Challenges for the 21st century*. New Delhi: Oxford University Press.

GoI, (2003). *Agricultural statistics—At a glance*. Directorate of Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India. New Delhi: Government of India.

Gosain, A. K., Rao, S., Ray, D. B., Bhandari, A., Calder, I.R., Amezaga, J.M., et al. (2006). *Hydrological modelling with SWAT model in the micro-watersheds of Madhya Pradesh and Himachal Pradesh*. Unpublished technical report, Indian Institute of Technology (Delhi) and University of Newcastle-upon-Tyne. Newcastle: CLUWRR.

Greene, W. H. (2002). NLOGIT—Version 3.0. Plainview, NY: Econometric Software Inc.

Heckman, J., Ichimura, H., & Todd, P. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies, 64*, 605–654.

Heckman, J., Ichimura, J., & Todd, P. (1998). Matching as an economic evaluation estimator. *Review of Economic Studies, 65*, 261–294.

Heckman, J., Ichimura, J., Smith, J., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica, 66*, 1017–1099.

Jalan, J., & Ravallion, M. (1999). Income Gains to the Poor. Estimates for Argentina's Trabajar Programme. World Bank Policy Research Working Paper 2149. Washington, DC: World Bank.

Jalan, J., & Ravallion, M. (2003). Does piped water reduce diarrhea for children in rural India? *Journal of Econometrics, 112*, 153–173.

Joshi, P. K, Jha, A. K., Wani, S. P., Joshi, L., & Shiyani, R. L. (2005). Meta-analysis to assess of watershed programme and people participation. Comprehensive Assessment Research Report 8. Colombo: IWMI.

Kerr, J., Pangare, G., & Pangare, V. L. (2002). Watershed development projects in India—An evaluation. Research Report 127, International Food Policy Research Institute. Washington, DC: IFPRI.

Manski, C., & Lerman, S. (1977). The estimation of choice probabilities from choice-based samples. *Econometrica, 45*, 289–306.

NSSO (2005). Situation assessment survey of farmers. Some aspects of farming. Report no. 496 (59/33/3), NSS 59th Round (January–December 2003), National Sample Survey Organisation, Ministry of Statistics and Programme Implementation, July 2005. New Delhi: Government of India.

Rosenbaum, P., & Rubin, D. (1983). The central role of the propensity score in observation studies for causal effects. *Biometrika, 70*, 41–55.

Rosenbaum, P., & Rubin, D. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician, 39*, 35–39.

Rubin, D. B., & Thomas, N. (2000). Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association, 95*, 573–585.

Turton, C., Warner, M., & Groom, B. (1998). *Scaling-up participatory watershed development: A review of the literature*. Overseas Development Institute, Agricultural and Extension Research Network, Paper No. 96 (pp. 20). London: ODI.

WaterAid (2005). Water and sanitation in Madhya Pradesh. A profile of the state, institutions and policy environment. WaterAid India. New Delhi: WaterAid.

World Bank (2003). India: Sustaining reform, reducing poverty. Washington, DC: World Bank.

World Bank (2004). Managing watershed externalities in India. Washington, DC: World Bank.

Available online at www.sciencedirect.com

ScienceDirect