EVALUATING SOCIAL IMPACTS OF WATERSHED DEVELOPMENT IN RURAL INDIA

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Abstract

Evidence of the social impacts of watershed development in India is often elusive. Watershed development alters land use patterns and the distribution of water access which, in turn, affects agricultural income and domestic water access. Using a propensity score matching method, changes in agricultural returns and domestic water collection times are estimated from treatment and control watershed data. Gross crop income is estimated to be US$11 less for a monsoon crop (kharif) and US$25 less for a post-monsoon crop (rabi) for the treatment watershed. While no significant variation is found across social, income or land groups for kharif data, impacts on rabi returns favour large landowners and prejudice small landowners and scheduled caste and scheduled tribe households. Domestic water collection in the driest months increases by 17 minutes per day, however the most water-stressed households reduce collection time by over 30 minutes per day. It is argued that careful targeting of poor watersheds is an insufficient condition to reduce poverty and watershed development design needs to manage competing water demands to effectively respond to rural poverty constraints.

Key words: India, poverty reduction, propensity score matching, 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

The two quotes illustrate the political priority and social challenges of watershed development in rural India. Watershed development has evolved to become a central approach to rural development and natural resource management with an annual spend greater than US$500 million (Kerr et al., 2002). Starting from a technocratic engineering approach in the 1990s, greater emphasis is now placed on societal considerations and participatory management of watershed projects, which are reflected in the 'Hariyali Guidelines' (GoI, 2003a). Yet objective evidence of the direction or magnitude of social impacts from watershed development is often unclear or disputed (World Bank, 2004; Kerr et al., 2002; Farrington et al., 1999). Benefits associated with watershed development include improved agricultural yields and farmer returns, increased access to domestic water and new employment opportunities. However, these benefits are likely to vary across resource user groups and seasons in most watersheds. This is partly due to interventions modifying land use patterns in semi-arid environments that will contribute to increasing water conservation in one place and reducing water availability for downstream users. 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 social groups.

Estimating social impacts of a watershed projects requires measurement of defined social outcome indicators conditional on the same indicators in 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 household in a treated watershed is the difference between an outcome indicator measured with the project and without it. Treated watershed

[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 (see NSSO, 2005)

data can be collected in a reasonably straight-forward manner once outcome indicators have been agreed, targets set and monitoring 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 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 (Rosenbaum and Rubin 1983 and 1985; Heckman et al., 1997 and 1998a; Jalan and Ravallion, 1999 and 2003; Baker, 2000; Deininger et al., 2004).

This paper estimates social benefits following watershed interventions in a treated watershed compared to a control group in a neighbouring watershed in Madhya Pradesh, India using a propensity score matching method. Three outcome indicators are considered: 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. The analysis attempts to gain a clearer understanding of 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.

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2. Evaluating social impacts of Watershed Development

Criticisms of watershed development projects mainly benefiting people with land has resulted in more inclusive ‘watershed plus’ approaches that broaden social benefits from improved agricultural yields or increased agricultural returns to also include improved access to drinking water, empowerment through creation of ‘thrift’ groups and non-land based employment opportunities (DANIDA 2004). Here, gross returns from agriculture (Rupees per seasonal harvest) and domestic water access (minutes collecting water in the dry season) will be evaluated to consider land and non-land based impacts.

2.1 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. 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 on the same individuals after project implementation. This method is followed in many watershed programmes 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 programmes, a counter-factual 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 (Rosenbaum and Rubin 1983 and 1985; Heckman et al, 1997 and 1998a).

Problems arise in both methods. Reflexive and double-difference comparisons are challenged by attrition, where a non-random sub-set 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 amongst those randomly chosen for the project. Matching methods can avoid these problems but create a different set of challenges. Reliability of matching estimates will depend upon:

- 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: 7) note that in the absence of these four features simple difference measures between participants and matched non-participants will result in a biased estimate of the project impact. A rigorous empirical example that compared bias from observed and unobserved characteristics indicated that bias in naïve estimates were huge but careful matching of the comparison group based on observables greatly reduced the bias (Heckman et al., 1998b).

2.2 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 are matched with non-participants in the non-treatment watershed. Survey data must include information that helps predict participation in the programme, 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 variables (*X)*, i.e. a match occurs where two individual from each sample record an identical match. This is likely to be rare and generally impractical (Jalan and Ravallion, 1999). Rosenbaum and Rubin (1983) show that matching can be performed conditioning on *P(X)* alone rather than on *X*, where *P(X) = Prob (D=1/X)* is the probability of participating conditional on X, the propensity score of *X*. Significantly, 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 and Lerman, 1978). 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 neighbour to the i^{th} participant is defined as the non-participant that minimizes $\{p(x_i - x_j)\}^2$ over all *j* in the set of non-participants. 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 matching only occurred over common values of propensity scores (Figure 1).

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

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

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

where Y_{j1} is the post-intervention agricultural return of household j, Y_{ij0} is the agricultural return of the i^{th} non-participant matched to the j^{th} participant, P is the total number of participants, NP the total number of non-participants and W_{ij} are weights applied in calculating average income of the matched non-participants. The matching estimator used is here a “nearest neighbour” 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.

2.3 Bias due to unobservables

The matching estimate described above may be biased if there are unobservables that jointly affect agricultural income and watershed participation. One approach to test for bias is to test for partial correlation between income and the residuals in the participation model (Jalan and Ravallion, 1999). An instrumental variables estimator treats placement as endogenous. The exclusion restriction assumed is that the instrumental variable is independent of outcomes given participation (Jalan and Ravallion, 2003). A regression is run on a combined sample of treated and non-treated households with income as the dependent variable and independent variables including the propensity scores, the residuals from the participation model and control variables from the participation model (Deninger 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) 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 and Ravallion, 2003: 159). The validity of testing for bias to domestic water benefits from unobservables seems less applicable than private land gains 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 income from unobservables will be tested.

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

3. Watershed Development in Madhya Pradesh

After India experienced steady agricultural growth of 4.8% (1992-1997), 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 one the poorest states in India with the majority of the poor living in rural areas and depending on agriculture and the natural resource base (DFID, 2004). NSSO (2005) estimate 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 (WaterAid, 2005; DFID, 2004). Improving agricultural productivity and returns in key crops such as paddy (monsoon crop or ‘kharif’) and wheat (post-monsoon season or ‘rabi’) to increase state-level yields appear feasible given that current yields are roughly half of national averages (GoI, 2003b).

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 state-level watershed developmet programmes that have been active in MP since 1994 and treated over 13,000 hectares of land in 249 micro-watersheds (< 500 hectares). One watershed treated from 1997 is the Dudhi watershed in Raisen district in central MP, neighbouring the Bewas watershed which is chosen as the control group for this evaluation analysis (Figure 2).

3.1 Study site

Selection of the Dudhi watershed involved collaboration between local government officials and the Rural Research Laboratory-Bhopal (RRL), which is a project implementing agency (PIA) for the state-level Watershed Development Mission. Selection criteria included water scarcity[5], a low level of development influenced by remoteness, high unemployment and a high proportion of SC/ST. A particular problem for the watershed population was shortage of domestic water in summer months due to public wells drying (Mr. R. Ram, personal communication, 2005). The Dudhi watershed has an estimated population of some 5,000 people and records significant variation in levels of illiteracy and employment and SC/ST inhabitants in each of the eleven villages (Table 1). The Bewas has a smaller population of

5 While mean annual rainfall is estimated at 1300 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).

some 3,000 people with one particularly large village (Searmau) and a similar variation in socio-economic indicators. Agriculture is a significant livelihood activity in both watersheds.

RRL provided data on activities conducted in the Dudhi watershed for infrastructure, employment generation and a post-project assessment of changes in kharif and rabi yields[6]. Responding to domestic water problems, a significant financial investment was made in pond construction accounting for US$81, 732 of infrastructure spend. 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, it is estimated that 2,575 hectares of private land and 1,203 hectares of public land were treated. While 94% of public land was treated compared to 73% of private land, the 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 578 hectares more rabi land (29%) were cropped following the intervention compared to an increase of 378 ha (19%) of kharif land. Impacts on average seasonal yields are estimated to be 84% higher (2 quintals[7] 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 labour spend, respectively. The aggregate employment days generated may be estimated at around 170,000 person days if a standard rate of R40 per day applied across all activities. Total watershed development expenditure is greater than US$260, 000 (R1.3 crore).

3.2 Data

In 2004, a post-evaluation survey was administered concurrently in the Dudhi and Bewas watersheds on which the following analysis is based. These data attempted to elicit 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 552 households in the Dudhi watershed and 226 households in the Bewas watershed. This is 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. In addition, the questionnaire recorded a

[6] Data tables available from the author.
[7] 1 quintal = 100 kg.

qualitative assessment of the social impacts of watershed interventions. This is useful in triangulating results from statistical analysis with wider comments from informants.

Data are explored to measure household effects of watershed interventions on kharif and rabi crop income[8] and access to domestic water in the dry months of March through July. Agricultural gain is clearly dependent on land access (own or lease) and as the kernel density estimation illustrates this is skewed toward households in the Dudhi treated watershed. A limitation of the agricultural income analysis is that relevant data were poorly captured across households in both samples, which resulted in a potential sample of 361 kharif farmers being reduced to 84 and 252 rabi farmers being reduced to 48 in the matching analysis. While the matching tolerance limit (0.01) and stringent data cleaning provide a reliable indication of intervention impacts this could have been improved by more effective data management. The domestic water matching sample was reduced from 573 to 470 households as fewer data inconsistencies or errors were encountered.

4. Results

4.1 Descriptive statistics

Descriptive socio-economic statistics of the treatment and non-treatment watersheds are presented in Table 2. Households in the treatment watershed report an average annual income of R12,233 (US$267[9]) with 42% derived from farm activities. This is reflected by higher land holdings and more farmers growing an irrigated rabi crop (33%) compared to the Bewas (19%). Irrigated area is on average (0.72 acres) higher in the Dudhi than the Bewas (0.25 acres). Ownership of bullocks and buffaloes is also higher in the Dudhi watershed where farming is more economically important. Bewas households gain the majority of income from non-farm sources with migrant income representing roughly one third of this income, a similar proportion to the Dudhi watershed. 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 development interventions on low income, agricultural dependency, poor domestic water access and a high population of SC/ST households.

[8] 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.
[9] All financial data are calculated US$1 = R50.

Perceptions of the impact of watershed interventions amongst the treated Dudhi is presented in Table 3. Responses centre on labour and water impacts. Coding identified five broad categories that reflect informant clusters of responses: 1) wage labour; 2) more water (generally); 3) water for livestock; 4) water for crops; 5) no benefit. Wage labour 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.

4.2 Propensity score matching estimates

Logistic regression model results are presented in Tables 4 and 6. Predictions for land ownership fit well with the descriptive data. As expected, living in the Dudhi increases the probability of owning land. Bullock ownership doubles the probability of owning land in Dudhi. Land ownership is less likely among SC/ST households. Probability of land ownership is not influenced by annual income in the model. More detailed socio-demographic data (e.g. education, health, residency, household composition, etc.) may have permitted a broader understanding though the model permits reliable propensity scores to be generated for matching purposes. The land model is tested for bias from unobservables. For identification, the location variable 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 agricultural crop income.

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 finding a sufficiently close match in the non-treatment sample and excluding missing or extreme value data. 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-treatment 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 to the non-treatment propensity scores (mean of 0.483 and standard error of 0.130).

The logistic regression model for water collection was specified by households spending more than 2 hours per day collecting water in the dry months of March through July. Results indicate that belonging to a 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 domestic water collection. This is most pronounced for farmers growing (irrigated) rabi crops, which appears logical. 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 a matched 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 neighbour estimate of the average impact across the sample is a loss of R534 (US$11) for a kharif crop and a loss of R1252 (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 R270 (US$5). Income stratification reveal no significant difference from the group mean though the poorest quintile report a loss (US$10) 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. 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, again 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 minutes per day. This impact is felt evenly by both social groups. Income stratification indicate a significant difference for the third quartile of 9 more minutes per day and 31 more minutes for the top income quartile.

Estimates for the bottom two income quartiles indicate small and non-significant time reductions. Finally, evaluating impacts against the existing distribution of water collection reveals that the interventions have most benefited those households with the highest 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 (lowest quartile) or 30 minutes more (second lowest quartile) collecting domestic water.

5. Conclusion

It can be expected that a land-based intervention that improves water conservation in one place will reduce water availability downstream. As watershed development in India (and elsewhere) becomes an increasingly favoured policy option for reducing rural poverty, non-local impacts (or externalities) are likely to become more pronounced as changes in water and land use patterns impact on other groups within and between villages. Clearer understanding of which interventions benefit particular groups, and by how much, will provide a firmer basis to manage land and water resources that are critical to natural, economic and social systems. Evaluating social impacts of watershed development is one element in the important process of managing land and water resources in an effective, efficient and equitable manner.

This analysis has illustrated the steps in applying a propensity score matching method to estimate social impacts of watershed development. The accuracy of the method is influenced by the closeness of fit between the treatment and control groups on economic, agro-climatic and social factors and application of the same survey instrument. While selection bias to unobservables cannot be rule out in any comparative analysis, there is evidence that this problem may be over-stated in practice (Heckman et al., 1998b; Jalan and Ravallion, 1999 and 2003). Without sufficiently detailed baseline data to evaluate project impacts, evaluating social impacts from cross-sectional data is considered suitable to matching methods.

Social impacts are estimated on agricultural crop income and domestic water access. These two indicators are purposively chosen to allow some understanding of the interaction between a land-based impact (likely to mainly benefit private land owners) and a public goods impact of domestic water access. Findings indicate no gain in either kharif or rabi crop income and an increase in domestic water collection compared to a non-treatment group of households from an adjacent watershed matched on their propensity scores. Some caution must be taken in interpreting these results due to possible bias from response errors such as strategic voting or protest votes after a watershed project has packed up and left. Careful data cleaning and matching has minimised this to some extent though the danger is highlighted by 75% of informant responses identifying project ‘wage labour’ or ‘no benefit’ in a qualitative evaluation of project impacts. Of equal concern, is the failure to capture agricultural yield data that would be a better indicator of project impacts, particularly to estimate food security impacts from households who do not market their crops. The ‘snapshot’ view that any one cross-sectional survey captures is also problematic though matching methods provides a defensible method for reducing bias from climatic or economic shocks that will influence farming system responses.

The developmental implications of this analysis suggest the watershed project has not contributed reducing poverty in the study villages. 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 stratification groups. The smaller group of rabi farmers fare even worse, on average, but significant variation is found across social groups and land ownership. Scheduled caste and scheduled tribe groups are estimated to be significantly worse off compared to other social groups. Households owning the most land benefit significantly (and positively) from the interventions while the bottom 50% of landowners are estimated to have income losses double, though not significantly different, from the sample mean. These results do not correspond well with own-project evaluations of a 84% increase in kharif yield and a 60% increase in rabi yield.

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 an acceptable level of domestic water access. Equally, a significant increase in collection times estimated from households in the lower collection quartiles suggests that while the general level of access has decreased the distributional access is more even. Investigating whether this lower level of domestic water access may be related to upstream water conservation structures diverting formally public access water to private land owners cannot be adequately addressed with these data, though this is a considered an increasingly common outcome of watershed development projects in semi-arid zones of India (World Bank, 2004).

A number of policy implications emerge from this analysis. First, careful targeting of watershed interventions in poor areas appears an insufficient condition to reach poor and vulnerable households. Second, while descriptive assessments may appear favourable, it is likely that biased evaluations of project impacts may result from assessments that do not account for observable and unobservable effects. Objective and rigorous social evaluation methods in the design phase of watershed projects will contribute to more defensible assessments. Third, by integrating social and biophysical assessments of projects in semi-arid areas, a clearer understanding of the impact of changes in land use patterns on water resource access will result, particularly the competition between agricultural demand and domestic water needs and the associated distribution of economic and social impacts. Finally, it is argued that if watershed development is to effectively release rural poverty constraints, the design and management of projects need to recognise and manage competing water demands in semi-arid rural areas over socio-economic, spatial and temporal criteria.

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References

Baker, J.L. (2000) Evaluating the Impact of Development Projects on Poverty. A Handbook for Practitioners. World Bank, Washington, D.C.

DANIDA (2004) Case studies and lessons learnt – Karntaka Watershed Development Project. DANIDA Watershed Development Programme, New Delhi.

Deininger, K., Hoogeveen, H. and Kinsey, B.H. (2004) Economic Benefits and Costs of Land Redistribution in Zimbabwe in the Early 1980s. *World Development* **32**, No. 10, pp. 1697-1709.

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

Farrington, J., Turton, C. and James, A.J. (1999), Participatory Watershed Development: Challenges for the 21st Century, Oxford University Press, New Delhi

GOI (2003a) Government of India, Ministry of Rural Development. 2003. Guidelines for Hariyali. Available at: www.nic.in

GoI (2003b) Agricultural Statistics - At a Glance. Directorate of Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, Govt. of India.

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

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

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

Kerr, J., Pangare, G. and Pangare, V.L. (2002) Watershed Development Projects in India – An Evaluation. Research Report 127, International Food Policy Research Institute, Washington, D.C.

Heckman, J. Ichimura, H. and 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. and Todd, P. (1998a) Matching as an Economic Evaluation Estimator. *Review of Economic Studies* **65**: 261-294.

Heckman, J., Ichimura, J., Smith, J. and Todd, P. (1998b) Characterizing Selection Bias using Experimental Data. *Econometrica* **66**: 1017-1099.

Manski, C. and 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, Government of India, July 2005. GoI: Delhi.

Rosenbaum, P and Rubin, D. (1983) The Central Role of the Propensity Score in Observation Studies for Causal Effects. *Biometrika* **70**: 41-55.

Rosenbaum, P. and 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. and Thomas, N. (2000) Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association* **95**: 573-585.

WaterAid (2005) Water and Sanitation in Madhya Pradesh. A Profile of the State, Institutions and Policy Environment. WaterAid India, New Delhi.

World Bank (2003) India: Sustaining Reform, Reducing Poverty. World Bank, Washington, D.C.

World Bank (2004) Managing Watershed Externalities in India. World Bank, Washington, D.C.

Figure 1. Kernel density estimation for land propensity scores

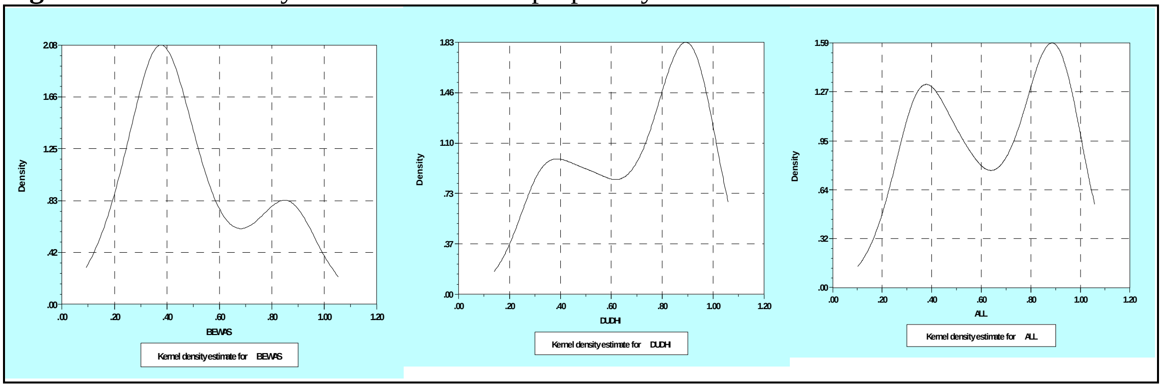

Figure 2. Location of study villages

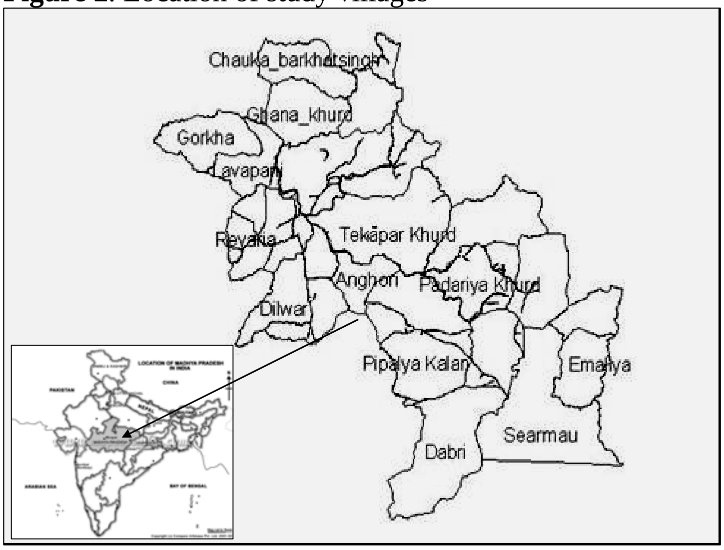

Table 1 Study village profiles

Village	Households	SC/ST (%)	Illiteracy (%)		Agriculture (%)	
			Female	Male	Cultivators*	Labourers
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

Legend: SC/ST – Scheduled caste/Scheduled tribe; * distinction implies ‘cultivators’ farm own land while ‘labourers’ are paid workers. **Source**: Government of India 2001 census.

Table 2. Descriptive socio-economic statistics

		Dudhi (treatment)	Bewas (non-treatment)
Total household income*		12,233 (420.94)	12,833 (1184.09)
Farm income		5,182 (359.65)	3,220 (779.91)
Off-farm income	All sources	7,051 (302.88)	9,613 (1068.55)
	Migrant wage	2,554 (185.50)	3,110 (615.66
Scheduled caste/ scheduled tribe		54% (0.02)	55% (0.06)
Land (acres)	All	5.67 (0.49)	2.60 (0.58)
	Irrigated	0.72 (0.12)	0.25 (0.13)
Grow irrigated rabi crop		33% (0.02)	19% (0.05)
Daily domestic water collection (minutes per day)	March-July	85 (3.57)	94 (11.46)
	Aug-Oct	47 (1.98)	48 (5.41)
	Nov-Feb	46 (1.80)	45 (5.29)
Bullocks (head)		1.13 (0.06)	0.67 (0.13)
Buffaloes (head)		0.46 (0.05)	0.22 (0.08)

Mean (standard error). Data are population-weighted averages. Financial data are Rupees per year for 2004 (post-intervention). *Income outliers (>R40,000 per year) are excluded.

Table 3. Dudhi villagers evaluation of watershed impacts

	Frequency	Percent
Wage labour	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.

Table 4. Logit model for land ownership

	Coeff. (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

** Significant at 1% level; *significant at 5% level.
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)

Table 5. Selection bias test for land model unobservables

	Coefficient	t-statistic
(Constant)	-17286.02	-8.03
Scheduled caste/ tribe	4557.45	4.81
Bullock	-3297.55	-6.07
Buffalo	351.04	0.83
Propensity score	33964.24	10.48
Residuals	-410.33	-0.42

Table 6. Logit model for spending more than 2 hours collecting domestic water in the period March-July

	Coeff. (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

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

Table 7. Estimated kharif and rabi income change by social, income and land groups

		Kharif income impact (n=84)	Rabi income impact (n=48)
Full matched sample		-536.90 (368.05)	-1251.56 (768.43)
Social	SC/ST	-270.00 (551.79)	-3055.83** (1045.41)
	Other	-779.55 (495.23)	1755.55* (628.58)
Income quartiles (Rupees per year)	Bottom	-550.00 (455.81)	-1766.67 (948.63)
	2nd quartile	-1263.64 (575.64)	-1127.08 (1570.19)
	3rd quartile	-1204.55 (560.86)	-2058.33 (1699.52)
	Top	1010.00 (1144.530	-54.17 (1903.48)
Land quartiles	Bottom	-766.67 (527.48)	-2333.93 (1339.45)
	2nd quartile	-888.46 (467.21)	-3887.50* (1174.51)
	3rd quartile	240.00 (558.87)	-1154.17 (1288.67)
	Top	-650.00 (1237.81)	3310.00* (184.60)

Mean (standard error). Based on nearest neighbour 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 (>R40,000 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%.

Table 8. Domestic water collection impacts by social, income and water collection groups

		Water collection impact[1] (minutes per day)
Full matched sample (n=470)		17.37 (2.46)
Social	SC/ST	18.32 (3.02)
	Other	16.19 (4.04)
Income quartiles (Rupees per year)	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 (4.4)*
	3rd quartile	15.57 (3.31)
	Highest time	-31.13 (3.16)*

[1]Positive values indicate increased collection times in March-July period, negative values indicate a reduction. Based on nearest neighbour propensity score estimation. Sample filter criteria: a) matched scores are accepted within a range of 0.01 points; b) extreme collection times (>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%.