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Modelling livelihoods and household resilience to droughts using Bayesian networks

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Abstract Over the last four decades, the Indian government has been investing heavily in watershed development (WSD) programmes that are intended to improve the livelihoods of rural agrarian communities and maintain or improve natural resource condition. Given the massive investment in WSD in India, and the recent shift from micro-scale programmes (<500 ha) to meso-scale ($\sim$5000 ha) clusters, robust methodological frameworks are needed to measure and analyse impacts of interventions across landscapes as well as between and within communities. In this paper, the sustainable livelihoods framework is implemented using Bayesian networks (BNs) to develop models of drought resilience and household livelihoods. Analysis of the natural capital component model provides little evidence that watershed development has influenced household resilience to drought and indicators of natural capital, beyond an increased area of irrigation due to greater access to groundwater. BNs have proved a valuable tool for implementing the sustainable livelihoods framework in a retrospective evaluation of implemented WSD programmes. Many of the challenges of evaluating watershed interventions using BNs are the same as for other analytical approaches. These are reliance on retrospective studies, identification and

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measurement of relevant indicators and isolating intervention impacts from contemporaneous events. The establishment of core biophysical and socio-economic indicators measured through longitudinal household surveys and monitoring programmes will be critical to the success of BNs as an evaluation tool for meso-scale WSD.

Keywords Bayesian networks (BN) · Watershed development (WSD) · Sustainable livelihoods · Natural capital · Drought resilience

1 Introduction

In drought-prone agricultural regions, water is critical for human consumption, irrigation and livestock supplies and for sanitation purposes (Wani et al. 2008). Across the developing economies, governments and non-government organisations (NGOs) have invested heavily in interventions aimed at maintaining and improving the natural resource base of drought-prone agricultural regions and enhancing the livelihood opportunities of local communities. For example, the Indian government has been investing in watershed development (WSD) since the 1970s and in the 2013–2014 financial year allocated 5387 crore (nearly 880 million USD) to the Integrated Watershed Management Programme (IWMP) (http://rural.nic.in/sites/downloads/budget/Budget_2013_14.pdf, Accessed 20/03/2014). Similarly, agricultural water management (AWM) programmes have been widely implemented across many African countries. These watershed interventions have largely been instigated in recognition of issues associated with food security for urban and rural regions, conservation or improvement of natural resource condition and the need to reduce the level of poverty in poor rural communities [e.g. Kerr (2007)]. In India, watershed development programmes typically implement technical interventions in the form of water harvesting structures or soil conservation methods which are intended to increase water availability and/or crop productivity (Kerr 2002; Palanisami and Kumar 2009). Social dimensions such as participatory planning, awareness building and capacity building have been incorporated since the 1990s (Bouma et al. 2007; Wani et al. 2008; Reddy et al. 2010), reflecting a global shift around this period of time from top-down approaches to rural development to bottom-up participatory approaches (Ellis and Biggs 2001).

In this paper, the Bayesian network (BN) approach is used to implement the sustainable livelihoods (SL) framework as part of a project investigating social and biophysical impacts of watershed development at the meso-scale in Andhra Pradesh, South India. BNs use a directed acyclic graph to represent dependencies between variables in a system and conditional probability tables (CPTs) to detail the relationship underlying each dependency. The approach is highly flexible and has been shown to have value in the analysis and modelling of socio-ecological systems where there is some reliance on qualitative knowledge during model conceptualisation and parameterisation or where the understanding of system processes is uncertain or incomplete [e.g. Chan et al. (2010), Kelly (Letcher) et al. (2013)]. Ticehurst et al. (2011) demonstrated the utility of the BN methodology in analysing survey datasets, in particular the capacity to develop insights around the presence and strength of causal relationships between landholder decision-making processes and policy outcomes. The model developed in this paper provides some evidence of positive impacts of WSD on indicators of natural capital and drought resilience although the size of the impacts detected by the model is less than the benefit perceived by surveyed households. Further, factors other than WSD are shown to be more influential.

The results we present are not definitive since demonstrating causality between interventions, capital indicators and resilience is complicated by a number of confounding factors previously identified in the literature including isolating the impacts of interventions from the impacts of other influences (e.g. other legislation, climatic variability, market prices), the range of livelihood strategies implemented by households and the timeframe over which the range of impacts occur and are measured (e.g. Reddy et al. 2004; Hope 2007; Kemp-Benedict et al. 2009; Nedumaran et al. 2013).

The remainder of this paper is structured as follows. Section 2 outlines some analytical tools, frameworks and modelling approaches that have been used to examine the effectiveness of watershed intervention programmes. Section 3 provides a brief history of WSD in India, including previous evaluation studies. Section 4 introduces the project of which the modelling described in this paper formed part of and describes the survey and model development methodologies. Section 5 focuses on the natural capital component, with discussion of the network structure and presentation of model analysis results. The relationship between the sustainable livelihoods capital types and household resilience to drought is examined in Sect. 6. The paper then concludes by drawing on the experience obtained from this work to make recommendations for future research and evaluation of WSD programmes.

2 Assessing impacts of watershed interventions

Despite significant investment in watershed management programmes, issues of food security and rural poverty remain prevalent and have the potential to be exacerbated by future population growth, changes to diets and climate change [e.g. Hanjra and Qureshi (2010)]. These development programmes are often implemented in highly complex, interlinked social and biophysical systems, and the programmes can influence the natural environment and people’s lives in a variety of beneficial or negative ways. Consequently, assessing the impact of development programmes on people’s wellbeing has received much attention [e.g. Kerr et al. (2002), Joshi et al. (2008), Nedumaran et al. (2013)]. Many authors have noted failures in documenting or systematically evaluating the effectiveness of intervention programmes with respect to achieving stated aims of poverty alleviation or enhanced livelihood opportunities [e.g. Baker (2000, p. iv), Rao (2000), Joshi et al. (2004), Adato et al. (2007)]. For example, Barron and Noel (2011) identified a lack of synthesised and documented evidence for increased agricultural productivity due to agricultural water management interventions and the need to evaluate programmes beyond the implementation area in order to account for off-farm and downstream impacts.

The noted deficiencies in assessments of watershed interventions are in part due to complexities introduced by confounding influences (or contemporaneous events), incomplete or imperfect knowledge, the spatial scale of impacts, and variability or diversity in natural and social systems. Watershed interventions are often one of many externally imposed factors influencing the system under study, and in practice it can be difficult to isolate effects of specific interventions. Common factors contemporaneous to WSD include changes in infrastructure and market access (Kerr 2002), concurrent programmes (Hope 2007; Reddy et al. 2004) and variability in natural and social systems. The difficulty in isolating effects of interventions is partially due to incomplete or imperfect knowledge about these systems. Wani et al. (2008) noted a ‘profound lack of baseline biophysical and socio-economic data beyond the typical focus on income, productivity, water enhancement and employment generation’ in most evaluations. Without baseline data, assessments may rely heavily on retrospective recall data from survey participants. Concerns have been raised about potential bias and reduced data accuracy associated with increased recall period [e.g. De Nicola and Giné (2014)], although it has been concluded that errors in recall data are to some extent both predictable and controllable (Bamberger et al. 2004). Even when baseline data are collected, there are potentially a large number of indicators that could be monitored but often interventions do not embody easily measured indicators (Nedumaran et al. 2013). Palanisami et al. (2009) noted that, due to the multi-faceted and complex impacts of watershed interventions, it "may not always be possible to measure the results that have been achieved because they may be intangible or it may be too costly to measure them effectively". While the impacts of watershed interventions on monetary incomes of the farmers or other households may be relatively straightforward to measure, livelihoods are often derived from common lands and other sources which can be difficult to value. Another issue complicating the monitoring of impacts is that the timeframe over which costs and benefits occur is not always clear (Nedumaran et al. 2013). Consideration of spatial dimensions is critical and focusing monitoring on the implementation area may lead to a false conclusion regarding the success of a programme. A programme may appear to be successful at village level but create negative externalities which outweigh the positive benefits received by the village (Syme et al. 2012). Variability in natural and social systems can obscure the effectiveness or impacts of interventions. For example, the magnitude of groundwater response to climate variability may mask the impact of interventions on groundwater. Similarly, being dynamic social systems, people may naturally rotate through different states of welfare. People also sustain themselves in a myriad of different ways and can respond to interventions in unexpected ways. Kemp-Benedict et al. (2009), for example, highlighted that the range of livelihood strategies employed by households to protect against shocks like drought can make designing and evaluating the impact of individual policy interventions difficult.

The need to assess development and NRM interventions has resulted in the development of a range of analytical impact assessment techniques and systematic frameworks intended to support programme design and monitoring and evaluation activities. Impact assessment or evaluation aims to measure the outcomes and impacts of development interventions by estimating what would have happened had the intervention not occurred (Baker 2000), while controlling for the aforementioned challenges typical of watershed development evaluations. *Ex ante* evaluations focus on assessing current or future interventions, while *ex post* studies retrospectively assess the impact of past interventions and can provide lessons to improve the design and implementation of similar interventions in the future (Freeman et al. 2005; Hope 2007). Randomised approaches, while considered the most statistically robust approach, are often not feasible for cost, ethical, political or practical reasons (e.g. where there are no control groups within a treated watershed). Consequently, non-random approaches are typically applied to assess impacts of individual watershed development programmes, either alone or in conjunction with qualitative approaches that elicit, from the target individuals or groups, perceptions of a scheme and its impacts on them. Non-random methods include reflexive comparisons which involve pre- and post-intervention sampling of treated groups and matching techniques such as propensity score matching [e.g. Hope (2007)] that can be used to identify a comparison group who has not received the treatment but are otherwise very similar.

Regardless of the selected impact assessment methodology, formal frameworks offer a transparent method for identifying key indicators and structuring assessments. Reed et al. (2005) identified many frameworks in the literature that focus on developing indicators for use in measuring progress towards sustainable development and poverty alleviation. The authors classified these as top-down expert-led (reductionist) or bottom-up (participatory) frameworks. The first category includes wellbeing assessments [e.g. Prescott-Allen (2001)] and the Drivers-Pressures-States-Impacts-Responses (DPSIR) framework [e.g. EEA (1999), Walmsley (2002)]. These approaches focus on quantitative indicators that reflect system complexities but do not focus on perspectives of resource users. In contrast, participatory approaches emphasise the local context in setting goals and establish priorities and an on-going role for communities and researchers or agencies in monitoring progress towards sustainability (Reed et al. 2005). One example of such an approach, the sustainable livelihoods (SL) approach, has gained increased attention in relation to the design, implementation and evaluation of watershed interventions. In 1999, the Department for International Development in the UK introduced the SL approach, based on Sen's entitlement theory (Scoones 1998). The SL framework has received considerable attention within the literature [e.g. Ellis (2000), Reddy et al. (2004)] and has been adopted by some governments and development agencies as a framework for evaluating linked socio-economic outcomes associated with adaptive co-management (Plummer and Armitage 2007). The SL framework is a holistic approach well suited to applications with a focus on assessing the range of livelihood impacts of interventions to an ecological system on communities [e.g. Binder et al. (2013)], including but not limited to economic impacts. It is used in this paper as the framework for the BN model development.

The SL framework assumes that people are living in a context of vulnerability relating to the nature and intensity of food and livelihood insecurity and that to ensure their wellbeing they must pursue a variety of alternative livelihood strategies, many of which are non-monetary. With the framework being based on the entitlement theory, vulnerability is explained in terms of the resources available to individuals or households; vulnerable households have an absence of resources (or entitlements) to cope with environmental or socio-political stressors [e.g. Adger (2006)]. The SL framework is aimed at providing an understanding of how a particular policy influences the dynamics within a system. When a programme is implemented, it may result in people being better off in some ways and worse off in others. Within the framework, the tangible assets (e.g. land, water, savings, livestock) and intangible assets (e.g. access to resources or services) that people use to generate wellbeing are divided into the categories of physical, human, social, financial and natural capital. Benefits to households from holding or possessing access to a resource are measured in terms of stocks and flows. Stocks are the amount of the resource, while the flows from a resource are the increases in overall stock that current levels of the resource are expected to generate over time. Flows from one capital are often seen as increases in the stock of another type of capital. When a programme is implemented, the framework allows improvements and trade-offs between the capital types to be explored. When household resilience against shocks, such as droughts, is improved without impacting negatively on natural resources, livelihoods are considered to be enhanced (Scoones 1998). The concept of resilience has been widely discussed in the scientific literature. Walker and Salt (2006) highlight the overall systems approach required to consider the successful management of interacting ecological and human systems. In general, we have followed this thinking but also followed their guidance on pragmatically applying this approach to key parameters which may define the overall vulnerability of human activities and ecological functioning. In this paper, resilience is defined as the number of drought years a household could survive without having to alter their means of livelihood. For example, a resilient farmer household could continue crop cultivation activities longer than a farmer household with low resilience. For landless households, resilience would be determined by their capacity to continue livestock production or undertake agricultural or other labour during prolonged drought periods.

Recent efforts have focused on operationalising the SL or other frameworks to allow quantitative measurements of indicators and comparison of intervention programmes with the view of informing the design and implementation of future intervention programmes. The overwhelming majority of impact assessment studies exploring the effectiveness of watershed or agricultural intervention programmes within the livelihoods lens, have involved the collation of survey data from households located within the implementation (treatment) area and nearby control areas using, for example, randomised control trials or other methods, and analysis of this data using econometric and regression techniques [e.g. Kerr et al. (2002), Reddy et al. (2004)]. More recently, other modelling approaches such as BNs [e.g. Newton et al. (2006), Kemp-Benedict et al. (2009)] and systems dynamics models (LaFlamme 2007) have been used in a limited number of studies to implement the SL framework. To our knowledge, the first study to detail the operationalisation of the SL framework using BNs was undertaken by Newton et al. (2006) to model the impacts of commercialising non-timber forest products on rural livelihoods. Similar to the approach taken in this paper, Kemp-Benedict et al. (2009) applied BNs using the SL framework to explore the links between water-related interventions and livelihood outcomes in a case study from the Si Sa Ket province in Northeast Thailand. Calder et al. (2008a) developed pilot BNs (although not framed using the SL approach) to develop common understanding between stakeholders on the causal linkages between factors that would be critical to the success of two WSD schemes in India and also to identify the potential for BNs to improve tactical decision-making over space and time. Other approaches used to model the impacts of policy interventions include the integration of biophysical and economic models, such as that of Nedumaran et al. (2013) who developed a bio-economic model of household's decision-making processes to simulate responses of households to the introduction of key technologies and policy interventions. Due to resource constraints, it is not always possible for practitioners or scientists to implement and analyse a suite of approaches and utilise the outputs from each of them to draw conclusions. Hence, selection of an appropriate approach should consider the strengths and weaknesses of each approach. In particular, the level of detail required to describe the system, the available types and quantity of data, and the spatial and temporal scale(s) at which impacts are to be analysed should be considered (Kelly (Letcher) et al. 2013). In this paper, the BN methodology is used as a tool for analysing socio-economic data collected using a retrospective non-random impact assessment based on the SL framework.

3 Evaluating watershed development in India

Increases in agricultural production in India before the second half of the twentieth century were achieved by expanding the area of production. Post 1965 a new strategy was implemented with the introduction of high-yield plant varieties, increased use of fertilisers and more widespread irrigation availability in many rural regions (Dhanagare 1987). Areas that were subject to these technological improvements experienced rapid increases in agricultural output. The investments that led to this enhanced productivity were purposefully focused on regions with favourable natural resource conditions [e.g. Fan et al. (2000)]. However, drought-prone rainfed agricultural lands received little investment despite being home to large numbers of people living in unfavourable economic conditions. Recognising this, the government of India commenced watershed development (WSD) programmes in the early 1980s as a means to increase productivity and socio-economic status in these areas. WSD became the focus for investment in rural development by the 1990s (Kerr 2002). Early WSD schemes focused on technical interventions imposed upon communities but evolved through the 1990s into a more participatory approach which explicitly incorporated social dimensions through capacity building and community engagement. Until recently, WSD programmes were designed and implemented for areas less than 500 hectares (the 'micro-scale'), a scale which matches with local communities (Barron and Noel 2011). In 2008, the Indian government re-designed their approach to WSD and now take a 'meso-scale' viewpoint whereby they promote clusters of WSD programmes at the scale of approximately 5000 ha within the Integrated Watershed Management Programme (IWMP) (GoI 2011).

Reflecting the situation across developing regions worldwide, there have been mixed outcomes reported for micro-scale WSD schemes in India which can be broadly classified as relating to the equity of the distribution of positive and negative outcomes or the impact on local or downstream water resources. Given that WSD is mainly a land-based intervention programme, direct and long-term benefits can be expected to flow to landholder households. Potential benefits for landless households from WSD could occur if the WSD interventions led to greater access to reliable and good quality common pool resources such as drinking water supplies, water for livestock or increased fodder or fuel availability and fuel. However, improved quality and reliability of access to water resources are not assured and Puskar and Thorpe (2005) noted that WSD has rarely provided much benefit to livestock-based livelihoods. Increases in cropped area and cropping intensity due to improved in situ moisture availability or irrigation (where recharge into groundwater has increased) post-WSD could result in increased farm employment or perhaps even higher wages [e.g. Palanisami and Kumar (2009)]. However, reported benefits to landless households are more commonly limited to short-term employment during the implementation phase of WSD programmes (Reddy et al. 2004; Calder et al. 2008a). Many authors have raised doubts as to whether households without land benefit from WSD in the medium to long term. This has led to concerns about the equity of WSD programmes. Kerr et al. (2002) evaluated the impacts of WSD by analysing household survey data from 350 households across 23 treated and six control villages and found that WSD had very little impact on the systems it was applied to. The authors thus challenged the assumption that WSD is beneficial to the natural resource base and agricultural productivity. They did, however, find evidence that programmes with a participatory approach performed better, but concluded that the poorest (landless) households received negative impacts from the programmes. Similarly, Bouma et al. (2007) randomly sampled 697 households across four meso-scale watersheds and identified that, despite being superior to top-down approaches, participatory approaches still failed to enhance the long-term sustainability of WSD. In another study, Reddy et al. (2004) studied the impact of WSD, also at village level, using the SL framework. In order to exclude poor implementation as a factor influencing outcomes, they focused on what were considered to be well implemented (or successful) WSD programmes. Some villages showed positive outcomes for some indicators, most notably increasing water tables despite low rainfall in the preceding 4 years and increasing bore numbers. None of the villages under study, however, were found to experience significant changes across all five capitals, despite being 'model' watersheds. Key issues related to the equity of any impacts and the authors concluded that while WSD programmes were necessary to strengthen the natural resource base, they needed to be implemented with other pro-poor programmes to effectively achieve livelihood and poverty alleviation goals.

Croke et al. (2012) conclude that most evaluations of micro-scale WSD in India are positive if the issue of scale is ignored and there has been a bottom-up approach gaining community ownership. However, detrimental impacts of WSD on water resources have been reported in the literature that has accounted for scale. For example, Batchelor et al. (2003) identified that in semi-arid areas WSD altered the spatial and temporal pattern of availability and accessibility to water, with any benefits traded off against substantial negative effects on availability in years with low rainfall. The authors identified WSD as contributing to groundwater depletion because activities focused on augmenting water supply and increasing access and demand for water. While irrigation benefited from WSD, the authors argued that other uses of water such as domestic consumption and livestock production were negatively affected. The reduced supply of domestic water was found to be particularly detrimental to the welfare of the vulnerable members of society, namely poor households and, women and children. The theory that the installation of rainwater harvesting structures changes the distribution of water availability was further supported by Calder et al. (2008a, b). Calder et al. found that downstream households appear to receive reduced water supply due to reductions in discharges from catchments as a result of WSD and, notably, that the poorest households also typically appear to receive reductions in supply.

4 Materials and methods

4.1 Meso-scale project

Implementation of WSD at the micro-scale has the advantage of enabling participation by local stakeholders. However, increasing the scale at which WSD is implemented from individual micro-scale schemes to clusters of micro-scale schemes designed and planned at the meso-scale is believed to provide a mechanism by which implementing agencies can explicitly consider and internalise hydrological and social externalities as well as achieve increases in administrative efficiency [e.g. FAO (2006), GoI (2011)]. Barron and Noel (2011) suggest that the meso-scale is where water quantity and quality impacts can be controlled and where the impacts of interventions will still be felt by local communities. There is some evidence to support this, although there is a need for research that informs the design and implementation of IWMP. This paper reports on a component of an integrated research project (here-on-in referred to as the meso-scale project) funded by the Australian Centre for International Agricultural Research (ACIAR) to investigate the nature and distribution of both benefits and negative impacts of past micro-scale WSD schemes across meso-scale hydrological units (HUNs) and communities by explicitly linking social research with biophysical modelling and hydrogeological characterisation to develop understanding of the connected biophysical, social and economic system. The project developed methods, procedures and recommendations to inform and guide the relatively new policy of IWMP which involves design and implementation of micro-scale programmes in meso-scale clusters (Reddy and Syme 2014).

The primary aim of the meso-scale project was to identify the critical issues associated with shifting intervention programmes from a micro- to a meso-level application. In the absence of existing 'meso-scale' designed and implemented projects, the project aimed to tease out meso-scale impacts of past micro-scale programmes by looking at impacts of WSD in upstream, midstream and downstream villages located within a hydrological unit (akin to watershed). The project considered the entire hydrological unit in order to quantify upstream–downstream linkages. The subsurface and surface hydrology and hydrogeological component of the project used geological, hydrogeological and geophysical techniques together with surface and groundwater hydrology modelling to assess the amount of available and accessible water across the hydrological units. From this, opportunities and constraints on water use were identified. It could reasonably be expected that the type and pattern of interventions for the micro-scale projects would differ from those adopted for a deliberately designed meso-scale cluster of WSD schemes. By combining hydrogeological analyses with a characterisation of biophysical resources (e.g. rainfall, land use, soil type), the project developed an understanding of the ideal types, density and location of WSD interventions at the meso-scale and contrasted this with the interventions that were actually implemented in the studied micro-scale schemes. Community impacts of WSD were interpreted at key locations representing the different hydrological opportunities at key sections of the watershed. While the socio-economic data were collected at the micro-scale, they were combined and contrasted within the overarching meso-scale hydrological unit. Using the socio-economic data, statistical analyses were used to identify relationships between WSD programmes and sustainable livelihoods and drought resilience as well as to explore equity of WSD impacts across the landscape

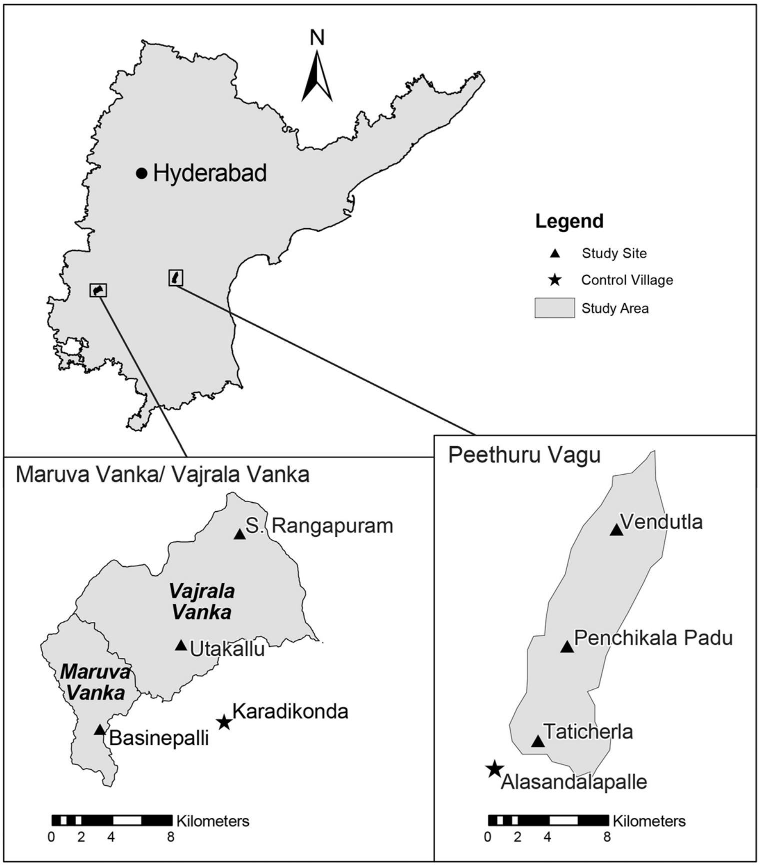

Fig. 1 Study sites

Table 1 Basic features and household sample selection in the sample villages [Adapted from Reddy and Syme (2014)]

Name of the village	Location within hydrological unit	Type of PIA	Year of formation	Year of completion	Village area (ha)	Watershed area (ha)	Population		Number of households[b]			
							Total	Scheduled tribe/castes (%)[a]	LL	SMF	LMF	Total
Anantapur and Kurnool districts												
S. Rangapuram	Upstream	NGO	1995–1996	1998–1999	339	816	466	34	10 (5)	11 (6)	66 (39)	87 (50)
Utakallu	Midstream	GO	1999–2000	2002–2003	1373	500	1523	14	37 (5)	140 (41)	143 (40)	320 (86)
Basinepalle	Downstream	GO	1998–1999	2003–2004	883	500	1955	29	175 (10)	139 (43)	111 (39)	425 (92)
Karidikonda (control)	Midstream	–	–	–	1351	–	1097	13	34 (4)	70 (18)	104 (24)	208 (46)
Prakasam district												
Taticherla	Upstream	GO	1998–2000	2003–2005	1903	500	1139	15	45 (10)	206 (78)	14 (06)	265 (94)
Penchikala Padu	Midstream	GO	2002–2003	2007–2008	974	500	491	10	22 (5)	87 (46)	05 (03)	114 (54)
Vendutla	Downstream	GO	1998–1999	2003–2004	2512	500	552	24	47 (05)	55 (36)	19 (13)	121 (54)
Alasandalapalle (control)	Upstream	–	–	–	1997	–	581	06	5 (5)	92 (30)	39 (12)	136 (46)

PIA Project Implementing Agency, *GO* government organisation, *NGO* non-government organisation, *LL* landless households, *SMF* small and marginal farming households, *LMF* large and medium farming households

[a] Scheduled castes and scheduled tribes are recognised in the Constitution of India as being communities that have been socio-economically disadvantaged due to historic social orders or, alternatively, geographic isolation or low agricultural or infrastructure development. The interests of these communities, and opportunities for improved socio-economic outcomes, require special consideration (http://ncst.nic.in/index.asp?langid=1, Accessed 17/06/2014)

[b] Figures in brackets are the number of households sampled in the resilience survey

and communities. Lastly, an integrated model based on the BNs described in this paper was developed to link key hydrological, biophysical and social–economic relationships and facilitate scenario analysis. Further details on the project components are provided in Reddy and Syme (2014).

4.2 Study sites

The meso-scale project studied the impacts of WSD across the landscape (from upstream to downstream regions) in two meso-scale watersheds (Fig. 1): the Peethuru Vagu hydrological unit in the Prakasam district, and the Vajrala Vanka and Maruva Vanka hydrological units which cross the Anantapur and Kurnool districts. Maruva Vanka is located downstream of Vajrala Vanka. 37–45 % of these hydrological units were treated with watershed interventions. In each watershed, three villages that had received WSD were selected as foci for the socio-economic data collection and analysis of impacts: these villages corresponded to upstream, midstream and downstream locations. The technical interventions that were implemented as part of the WSD programmes include the installation of check dams, tanks (in Prakasam), kuntas and farm ponds. Check dams are structures that capture surface runoff water and encourage percolation into groundwater. Tanks are large surface structures that harvest and store rainwater. Kuntas are small depressions of low porosity used to capture water for livestock, and farm ponds are an excavated rainwater harvesting structure used for irrigation. In addition to WSD, each village was covered under the Andhra Pradesh Farmer Managed Groundwater Systems (APFMGS) programme which was designed to promote sustainable management of groundwater by farmers through building their skills and knowledge. A control village that had not received WSD but was part of the APFMGS programme was selected for both watershed locations. The basic features of the study and control villages are listed in Table 1.

A randomised approach was not possible for the selection of the hydrological unit and sample villages in the meso-scale project. In discussion with the Andhra Pradesh Department of Rural Development, the hydrological units were purposively selected such that the treated area in the selected micro-scale WSD programmes would correspond to the coverage of treatment expected from future IWMP implementation. Sample villages were selected based on considerations including the presence of watershed structures and land use. While the generalisation of findings from this study may be reduced in comparison to site selection using randomised control trials, drawing a random sample was not possible given the lack of meso-scale hydrological units with suitable levels of treatment covering the upstream-to-downstream continuum. Further details on the process used to select the study villages are provided in Reddy and Syme (2014).

4.3 Household resilience survey

A survey of 522 households from the six WSD and two control villages was carried out during November 2011 to elicit the impacts of WSD on the households' stocks of key capital assets and their resilience to drought. The surveyed households were selected randomly from within the sample villages.

Details on the survey and sampling methodology are provided in Reddy and Syme (2014). In overview, the design of the household survey was based on the SL approach and focused on capital assets that vary at the household level and which could reasonably be expected to be impacted by WSD. The SL framework was adopted to facilitate the mapping of socio-economic consequences of changes brought about by WSD interventions. Prior to undertaking the survey, focus group discussions were used to assess the potential and clarity of the SL approach, as well as to guide the selection of survey questions. The indicators of household capitals explored through the survey were linked to explicit goals of the implemented WSD programmes. These goals were strengthening the natural capital base (increased availability of water, fodder, fuel, etc.), improving social capital (group membership, etc.) and human capital (enhanced expenditure on education and health) and increasing land productivity (financial capital). In addition, the survey questions were defined using the projects' social scientists knowledge of the spectrum of livelihood and environmental indicators that may be expected to change in response to WSD interventions, as well as from indicators defined in the literature [e.g. Farrington et al. (1999), Rao (2000), Turton (2000), Reddy et al. (2004), Reddy et al. (2010)]. The survey covered topics relating to cropping activities, employment opportunities and income streams, watershed-related resilience and household stocks of capital assets and the reliance of households on these stocks to support livelihood activities during droughts. Responses from the survey were directly used in the BN model development (Table 2).

4.4 Model development

The remainder of this paper focuses on the use of household survey data to develop a BN based on the SL framework. Focusing on natural capital and the linkages between the five capitals and drought resilience, we use the model to explore impacts of WSD in the study villages, and compare the magnitude of changes against household-perceived value of

Table 2 Overview of household resilience survey questions used in BN model development

Theme	Question	Use of survey responses in model development
Household details	Irrigated and non-irrigated land area; cropping pattern (Q1)	Financial, natural and physical capital
Cropping	Recent history (last three years) of crop loss or poor production (Q3)	Financial capital
Income and employment	Household consumption and investment in agriculture (Q5)	Financial, human, natural and physical capital
	Supplementation of income through off-farm income (Q6)	Financial capital
	Employment/income of household members (Q7)	Financial capital
	Previous history of accessing additional sources of income during droughts (Q11)	Financial capital
Watershed-related resilience (asked only of WSD villages)	Access to and benefits gained from common pool resource (CPR) forests (Q12)	Financial and natural capital
	15. Consecutive number of drought years that could be 'survived' with and without WSD (Q15)	Resilience
Resilience and stocks of capital indicators	Stock of the five capital indicators over the previous 6 years (Q16)	2010–11 stocks used to model all capitals
	Extent of reliance on each capital stock to survive consecutive drought years (Q17)	All capitals

WSD and some simplified scenario modelling of livelihood impacts of land redistribution policies.

The theoretical basis of BNs has been widely described within the literature [e.g. Cain et al. (1999), Bromley et al. (2005), Kjaerulff and Madsen (2008), Korb and Nicholson (2011)]. Chen and Pollino (2012) provide useful guidelines for the development of BN models to support evaluation of environmental systems with particular focus on model conceptualisation, development of the network structure, treatment of model uncertainty and model evaluation. BNs were selected as the integration tool in the meso-scale project primarily because they are well suited to integrating different types of data. In this paper, they are used to link knowledge and model outputs from hydrological and biophysical knowledge and household livelihood indicators to drought resilience. The suitability of BNs for modelling environmental problems through integration across issues or disciplines with high uncertainty is now widely documented [e.g. Bromley et al. (2005), Castelletti and Soncini-Sessa (2007), Henriksen et al. (2007), Ticehurst et al. (2011)]. BNs are most suitable where qualitative information is used in (part or all of) the model parameterisation

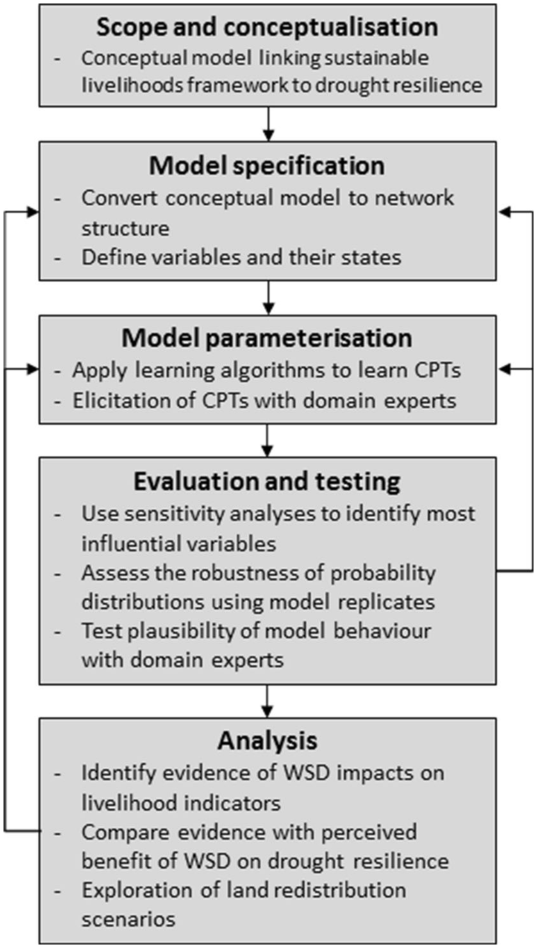

Fig. 2 Iterative model development process

process, where the understanding of system processes is uncertain or incomplete, where the focus of the modelling exercise is to look at aggregated affects and where it is not essential to represent dynamic processes or feedbacks in the model (Kelly (Letcher) et al. 2013). When representation of dynamic processes is considered critical or the focus is on the interactions of individuals (or agents), then the other approaches commonly utilised in integrated modelling may be more appropriate (e.g. agent-based models, systems dynamics or coupled component models). In this paper, the focus is on the modelling of aggregated responses for household classes rather than impacts of WSD on, or the behaviour of, individual households. These systems are dynamic with factors like climate variability and groundwater extractions influencing water availability and crop productivity over time, and impacts of WSD can be short term (e.g. labour) or more long term. However, given the household surveys represent a snapshot in time, BNs are a useful and appropriate tool for exploring relationships in the data.

The model development process followed the guidelines for good modelling practice for environmental modelling in general (Jakeman et al. 2006) and BN modelling in particular (Chen and Pollino 2012). The definition of the scope and scale of the modelling drew on an early conceptual diagram developed by the research team which scoped how each component of the meso-scale project would fit together (Croke et al. 2012). The key objective of the socio-economic component was to capture household decisions and household–village scale outcomes, measured by indicators of resilience, equity and the five capitals, and the impacts of household decision on water resources at the subcatchment scale. An

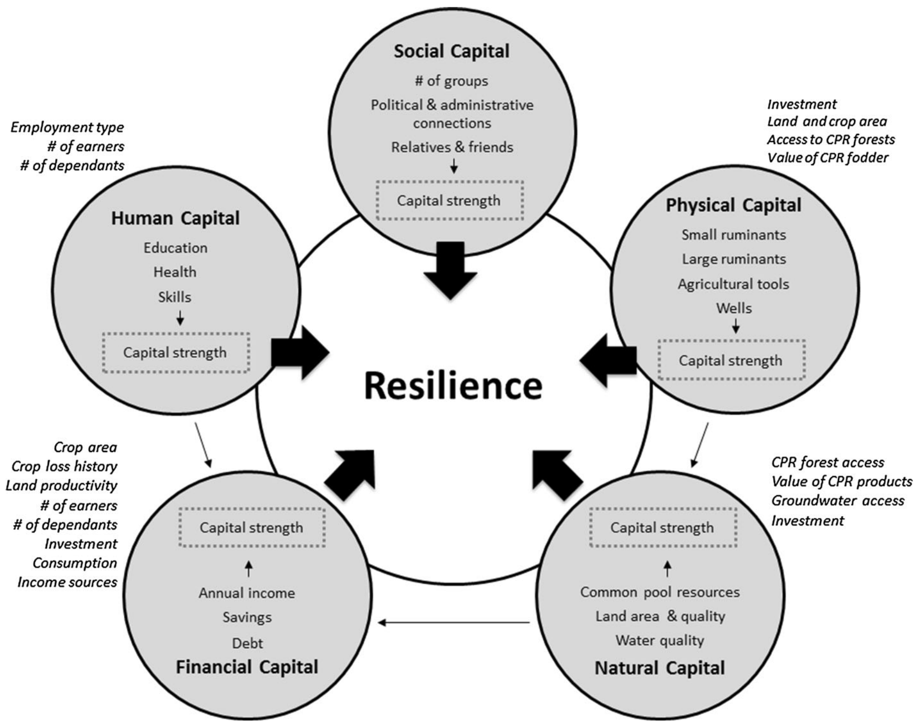

Fig. 3 Structure of the capital strength and resilience BNs: sub-model BNs for each type of capital are linked to the capacity of households to survive consecutive drought years (resilience)

initial graph structure, or influence diagram, for the BN model was defined based on the conceptual model and the sustainable livelihoods framework. After the model variables, variable states and network structure were initially specified the model was parameterised using the household survey data with some expert input. Expert input was used when variables were of a nature that could not be determined from individual household responses: for example, for aggregation nodes (see Sect. 4.4.2) or for biophysical variables such as the potential access to groundwater (see Sect. 5). The model was evaluated qualitatively by domain experts within the project team and using quantitative measures such as sensitivity analysis based on the mutual information statistic. The development process was highly iterative with all stages of model development used to refine the model structure and definition of variable states (Fig. 2).

4.4.1 System conceptualisation and network structure

Given the aforementioned focus on equity and resilience, the BN described in this paper was constructed to develop relationships between capital indicators of livelihoods and household resilience and to explore the impacts of WSD across the landscape (i.e. the upstream, midstream and downstream villages in two hydrological units) and household types. In accordance with the household survey, the SL framework is used as the conceptual framework on which the BN model structure is based (Fig. 3). Household resilience to drought is affected by the livelihood stocks that a household can employ to maintain their activities; these stocks are broken down into the five types of capital shown in Fig. 3. The key stocks shown within the circle for each capital type (e.g. agricultural tools, ruminants and wells for physical capital) correspond directly to questions in the survey (Question 16 in Table 2) and were identified by the lead social scientists in the project (one of the co-authors) as critical indicators of livelihoods in these regions using outcomes from focus group discussions and past research [e.g. Reddy et al. (2004)]. The factors influencing these stocks, noted in italics next to the five capitals in Fig. 3, were identified in the model conceptualisation phase from the household questionnaire. For example, stocks of the physical capital assets are influenced by access to common pool resource forests (and harvested fodder from these forests) in addition to the level of agricultural investment and the area of owned land and cropping.

Sub-models have been developed for each type of capital; these sub-models all have the same hierarchy of network variables. As the intent of the model was to discriminate WSD impacts across the villages and households, the input variables to the model (termed household class variables) describe whether or not the household lives in a village that has received WSD (*Watershed development*), the hydrological unit in which the household lives (*Hydrological unit*), the location of the household's village within the hydrological unit (*Location*), the economic status of the household using farm size as a proxy (*Economic category*) and the household caste (*Social category*). Household class variables affect the capital stock variables, either directly or through the factors identified as influencing the capital stocks. The capital stock variables are defined as the level of stocks—for example, the number of small ruminants—owned by the household in 2010–2011. These stocks will help households maintain their livelihood activities during stresses such as droughts although for how long depends on the type and amount of the stock the household owns. Reflecting this in the BN sub-models, capital stock variables are the parent variable of drought support variables which describe the number of consecutive droughts that the stocks of a particular capital indicator will continue to support a household's ability to continue their livelihood. These variables are linked to the terminal node of the model—*Resilience*, the number of consecutive drought years a household could maintain their livelihood activities—through aggregate nodes describing the 'strength' of each capital type. These variables are included to keep the size of the CPTs for the *Resilience* variable to a manageable level. The *Resilience* variable is used to integrate the capital sub-models and explore the relative importance of each type of capital in the villages. The structure of each of the sub-models was developed using this hierarchy and iteratively refined based on the review by the social scientists in the project team and outcomes from evaluation of the sub-models.

Once the network structure was developed, the states for each of the network variables were then defined. Categorical responses to questions in the household survey were used directly to define of states for relevant variables, for example, the household self-assessment of the adequacy of drinking water stocks as 'Not applicable', 'More than adequate', 'Adequate' or 'Inadequate'. Continuous variables such as land area, investment in land (in Rupees) or the monetary value of fodder collected from common pool resource (CPR) forest lands were discretised into a finite set of states which were tested to ensure that the states of variables directly affect, or were affected by the states in, linked variables and that the states were relevant to model objectives and consistent with understanding of the socio-economic system being modelled.

4.4.2 Model parameterisation and evaluation

The survey answers from each household respondent were used to develop a case file that was used to parameterise the majority of variables in the network. The majority of the CPTs were learnt using the Expectation Maximisation (EM) algorithm (Dempster et al. 1977). This algorithm assigns a uniform distribution to each row of the conditional probability table (equal probability of all states) and then adjusts the probabilities based on the imported data to maximise the probability of the model obtained being the one that represents the system that generated the data (i.e. it finds the maximum likelihood estimate of the parameters). In data scarce situations, Koller and Friedman (2009) considered this approach more reliable than other algorithms such as the Lauritzen and Spiegelhalter (1990) algorithm. Chen and Pollino (2012) showed that when no appropriate datasets or models exist with which to parameterise the CPT table of a variable within a BN, it is valid to base the values within the CPT on expert opinion. Although this may not be as rigorous as the parameterisation based on data, it allows for current beliefs about how the system operates to be communicated in a transparent manner. In this study, the capital strength variables were defined in this way. The survey respondents were asked, for each capital asset, how long their current (2010/2011) stocks of that asset would continue to support their survival during consecutive drought years (0, 1, 2 or 3 droughts). Households were asked to identify the most important capital type (e.g. natural capital) and indicator (e.g. water) in terms of supporting the long-term sustainability of their livelihood activities. These results were used to scale the influence of the capital indicators on the overall drought support provided by the capital. If the weighted sum is less than 2 (i.e. drought support provided by the capital is less than 2 years), then the capital is defined as 'Weak'.

Once parameterised, the BN sub-models were evaluated using (i) review of the plausibility of model relationships using scenario analysis, (ii) sensitivity analyses based on the mutual information (MI) statistic and (iii) an assessment of whether the BN relationships are (or are not) robust to sample size. The model was qualitatively evaluated by looking at how probability distributions in the network change with different combinations of inputs and reviewing the model assumptions and model behaviour in workshops with the disciplinary researchers in the project team and key agency and NGO stakeholders. The MI statistic was used to summarise the strength of the relationship between each child node and its parents. When one variable depends on others, it is called the child node of each of the others, its parents. The MI between a child node and a parent node is defined to be the average (across the parent node states) of the total change in probability experienced by the child node states when the parent node is set to a particular state. If the child node does not depend on the state of a parent, then the MI between the variables will be 0. MI was used to evaluate whether or not to include links in the network and also to compare those links which were included. We call a child node 'sensitive' to a parent node when it has relatively high MI with that parent node compared to other links in the network. When links were found to have relatively small MI, their inclusion in the network was subject to review. Hypothetically, if the *Functioning wells* variable in Fig. 4 has *Economic category* as a parent, and the MI for this link was considerably smaller than other MI statistics in the network, then the link between these two variables might be removed to reduce the overall model complexity. This process is one of the ways that the BN modelling methodology allows users to obtain qualitative information about a system, as the model is iteratively constructed. Lastly, the sensitivity of model relationships to sample size was examined by replicating the model 20 times, with each replicate having the data-based CPTs learnt using 417 cases (~80 %) selected at random from the complete dataset. The variation in the CPTs and unconditioned beliefs across all replicates was examined to provide information on how reliable the current quantity of data is and which variables (parameters) are most affected by sample size. Note that this simple sensitivity test differs from cross-validation tests, whereby the predicted probability of states for pre-selected (unobserved) variables using the training data is compared with the observed proportions in the validation data.

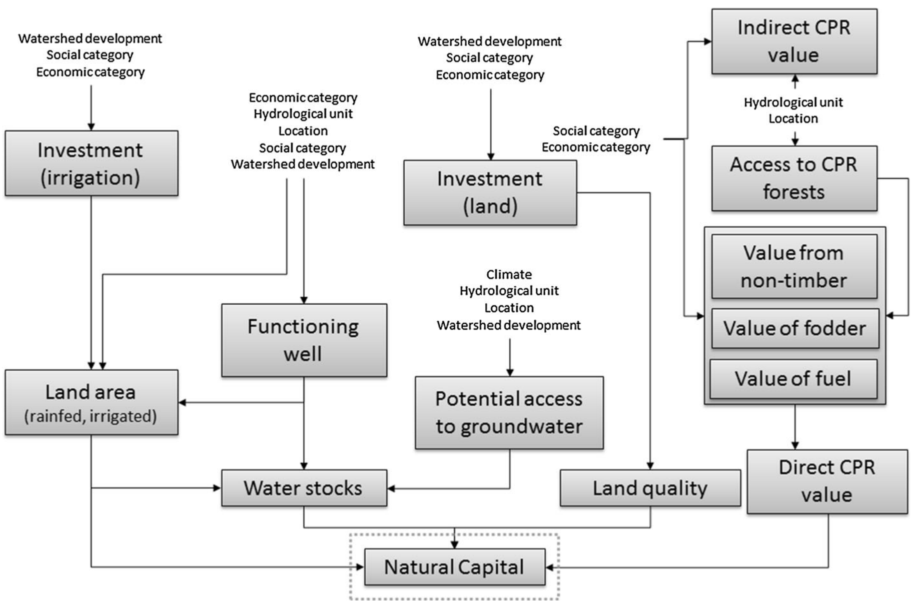

Fig. 4 Conceptual model of the natural capital sub-models. The *dashed box* indicates that indicator stock variables are linked to the capital strength variable through drought support variables which describe the number of consecutive droughts that the stocks of a particular capital indicator will support a household's ability to maintain their livelihood activities

5 Natural capital

5.1 Network structure

In agricultural regions of India, such as Andhra Pradesh, natural capital is a critical determinant of the livelihoods of rural people who directly depend on land and water resources through cropping, raising of livestock or hunting and collecting (e.g. Reddy et al. 2004). Natural capital is closely linked with the other types of capital, particularly human capital through impacts on direct subsistence, health and wellbeing as well as physical capital and financial capital (Baumann 2000). The indicators of natural capital represented in the sub-model are the area and quality of land that households own, the quantity of water resources available to the household and the direct value of common pool resources (CPR) accessed by each household (Fig. 4). Most households who reported natural capital as the key determinant of their sustainability identified water as being the critical indicator (57 %), followed by land (38 %) and CPR (5 %). These data were used to scale the influence of the drought support variables on the strength of natural capital. In the study areas, households' access fodder, fuel and to a lesser extent non-timber products from CPR forest areas; access depends on proximity to forests which differs between villages (*Hydrological unit* and *Location*). Also represented in the network, with the same parent variables, is the indirect value gained from CPR forests (e.g. protection against soil erosion). The fodder, fuel and non-timber components are related to the total 'direct' CPR value reported by the households. *Land quality* is the child node of (i.e. has direct links from) the *Location*, *Economic category, Social category* and *Investment in Land (Rs)* variables. In the survey, participants were asked to rate the adequacy of their household water stocks (*Water stocks*). This is a social variable, and responses reflect how they use (or wish to use) water (e.g. for irrigation) and the availability of water resources. This variable is connected to the *Potential access to groundwater (%)* variable, which is defined as the maximum percentage of wells within a village area from which water could be extracted under dry, normal or wet climate years, in order to connect the social and biophysical aspects of the issue. This biophysical variable has been populated using expert elicitation from hydrologists and water resource scientists in the project team and is further related to the geographic variables, *Location* and *Hydrological unit*, as well as *Climate* and *Watershed development*. The *Climate* variable is based on the percentage departure from average annual rainfall and has the states of 'Deficit' (<−19 %), 'Normal' (−19 to 19 %) and 'Above Normal' (>19 %). The influence of land area on supporting household drought resilience is defined in terms of both irrigated and rainfed area. Whether or not households own functioning wells and the extent to which they invest in irrigation influences the area of land under irrigation. *Functioning wells* is the child variable of the *Location*, *Hydrological unit, Watershed development*, *Economic category* and *Social category* variables, as is the *Land Area (acres)* variable. A definition of each variable and its states is given in Table 5 in Appendix.

5.2 Results

5.2.1 Sensitivity analysis and model evaluation

The sensitivity of the *Natural capital* variable to all other variables in the network is shown in Fig. 5. The group of variables to which Natural capital is most sensitive include the drought support variables for land area and water quantity. Given these variables are directly linked to *Natural capital*, it is expected that they will be more influential than variables which are not directly linked (as explained by Marcot et al. 2006). However, the *Drought support (CPR)* variable is much less influential than the other drought support variables due to the low weighting given to the variable which reflects its lesser importance in the sustainability of the household's activities. Also influential are the *Irrigated area* and *Functioning wells* variables.

As outlined in Sect. 4, the entirety of the available cases was used to parameterise the model. The test to explore sensitivity of the model parameters to sample size using replicates with randomly selected subset of the data yielded only minor variations (<0.03) in the likelihood of variable states for most variables in the network. The variable most affected was *Irrigated area (acres)*. Across the 20 models, the likelihood of zero acres of irrigated land varies from 58 to 68 %, while the likelihood of 0–5 acres and ≥5 acres categories vary from 25 to 31 % and 6 to 11 %, respectively. The irrigated area variable is more susceptible to smaller sample sizes compared to other variables in the network as it is only relevant to about one third of the surveyed households. However, this test indicated that most of the CPTs in the natural capital sub-model that were learnt using the EM algorithm are reasonably robust to the sample size.

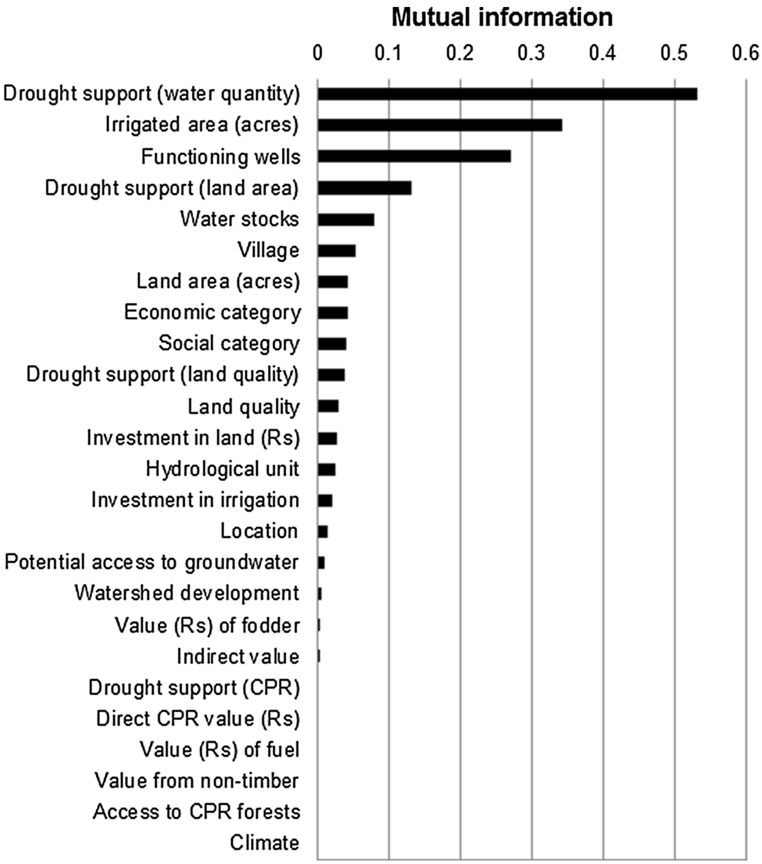

Fig. 5 Sensitivity of natural capital to variables in the BN

5.2.2 Common pool resources

The natural capital assets that households from all economic categories can access are those sourced from CPR resources. While the modelled likelihood of households possessing weak natural capital across the survey population is 82 %, it is slightly higher for households who report that the stocks of CPR forest resources (as an annual value in rupees) that they 'own' would only support household survival of 'One drought' (86 % likelihood of weak capital). Across all economic categories, the major components of CPR resources that the survey households access are fodder for livestock and timber for fuel; less than 2 % of households access non-timber resources. This is reflected in the greater influence of the fodder (MI = 0.661) and fuel (MI = 0.708) variables on the direct economic value gained from CPR resources compared with non-timber uses (MI = 0.003). 51 and 74 % of households collect fodder and fuel from CPR forests, respectively.

Over the last decade, the redistribution of land identified "excess" and "wastelands" including CPR areas to landless households has been a policy initiative that has been implemented in Andhra Pradesh. Without appropriate management, the resultant clearing of vegetation on these lands could be expected to increase surface runoff and reduce groundwater recharge. If this policy was to be implemented in the Prakasam hydrological unit, then landholder households would incur losses of value arising from access to CPR forests; 58 % reported an annual direct CPR value of greater than 4000 Rupees. Landholder households also gain indirect value from CPR forests, namely through mitigation against erosion. In Prakasam, 53 and 41 % of small–marginal and medium–large households, respectively, report such benefits from CPR forests. In the model, losing direct value from CPR forests translates to a reduction in the likelihood of strong capital from 23 to 17 % for small–marginal farmers and 62 to 52 % for medium–large farmers. This needs to be balanced against potential livelihood opportunities for landless communities from increased access to natural capital assets such as land and water. Currently, the modelled strength of natural capital, based on the characteristics and capital assets of landless households in Prakasam, has a 100 % likelihood of being 'Weak'. Assuming implementation of the policy would shift these landless households to small–marginal households with no access to CPR forests and no investment in agriculture or access to functional wells, then the modelled likelihood of 'Weak' natural capital decreases marginally to 98 %. With investment in agriculture and access to functional wells at the level reported by the current small to medium, more substantial decreases in the likelihood of 'Weak' natural capital are modelled (83 %).

5.2.3 Impacts of WSD

The sensitivity analysis in Fig. 5 suggests that the watershed development variable exerts less influence on the model outcome (strength of natural capital) relative to other household class variables. In the natural capital BN, *Watershed development* is a parent of five variables: *Land area (acres)*, *Functioning wells*, *Potential access to groundwater (%)*, *Investment in irrigation* and *Investment in land*. All of these variables are more influenced by changes in other variables (Table 3). Land area and investment in land are most sensitive to the *Economic category* (i.e. farm size), while the potential accessibility of groundwater is most influenced by *Climate*, then *Hydrological unit* and *Location*. In the Prakasam hydrological unit (Fig. 6a), the potential access to groundwater in the upstream control village is quite limited with only 5–20 % of bores at the village level operational; the upstream WSD village has a similar potential access to groundwater although there is a small likelihood (0.06) of more reliable access (60–100 %) in part of the village area. The majority of survey households are small to marginal farmers (<5 acre): 61 and 81 % in the control and WSD village, respectively. In the Anantapur–Kurnool hydrological unit (Fig. 6b), access to groundwater is less reliable in the WSD village than in the control village, while 39 and 52 % of sample households from the WSD village are small to marginal farmers and medium to large farmers, respectively, compared with 58 and 36 %, respectively, in the control village. Households from the WSD village in Prakasam report a higher incidence of well ownership, investment in irrigation, investment in land development and area of irrigated land than households from the control village. A similar pattern of higher investment and more irrigation in the WSD village compared with the control village is seen in the Anantapur–Kurnool hydrological unit. However, there is relatively little difference in the modelled likelihood of natural capital between the control and WSD villages (1 % in Prakasam and 4 % in Anantapur Kurnool).

Focusing on Prakasam, where the control and WSD villages have similar access to groundwater, the greater likelihood of farming households undertaking irrigation and reporting ‘adequate’ water stocks in the WSD village compared with the control village is consistent across the castes although the magnitude differs (Fig. 6c, d). Scheduled caste households in the control village do not invest in irrigation or own functional wells and irrigate little (if any) of their land (Fig. 6c). In the corresponding WSD village, about half of the scheduled caste households irrigate some of their land. This reflects some likelihood of functional well ownership (47 %) and investment in irrigation

Table 3 Influence of WSD and other household variables on child nodes

Variable	Sensitivity (descending order)
Land area (acres)	Economic category (1.21)
	Social category (0.071)
	Hydrological unit (0.069)
	Watershed development (0.014)
	Location (0.010)
Functioning wells	Social category (0.083)
	Hydrological unit (0.071)
	Economic category (0.063)
	Location (0.038)
	Watershed development (0.028)
Potential access to groundwater (%)	Hydrological unit (0.190)
	Location (0.480)
	Watershed development (0.070)
	Climate (0.002)
Investment in irrigation (Rs)	Social category (0.080)
	Economic category (0.060)
	Watershed development (0.035)
Investment in land (Rs)	Economic category (0.466)
	Social category (0.046)
	Watershed development (0.006)

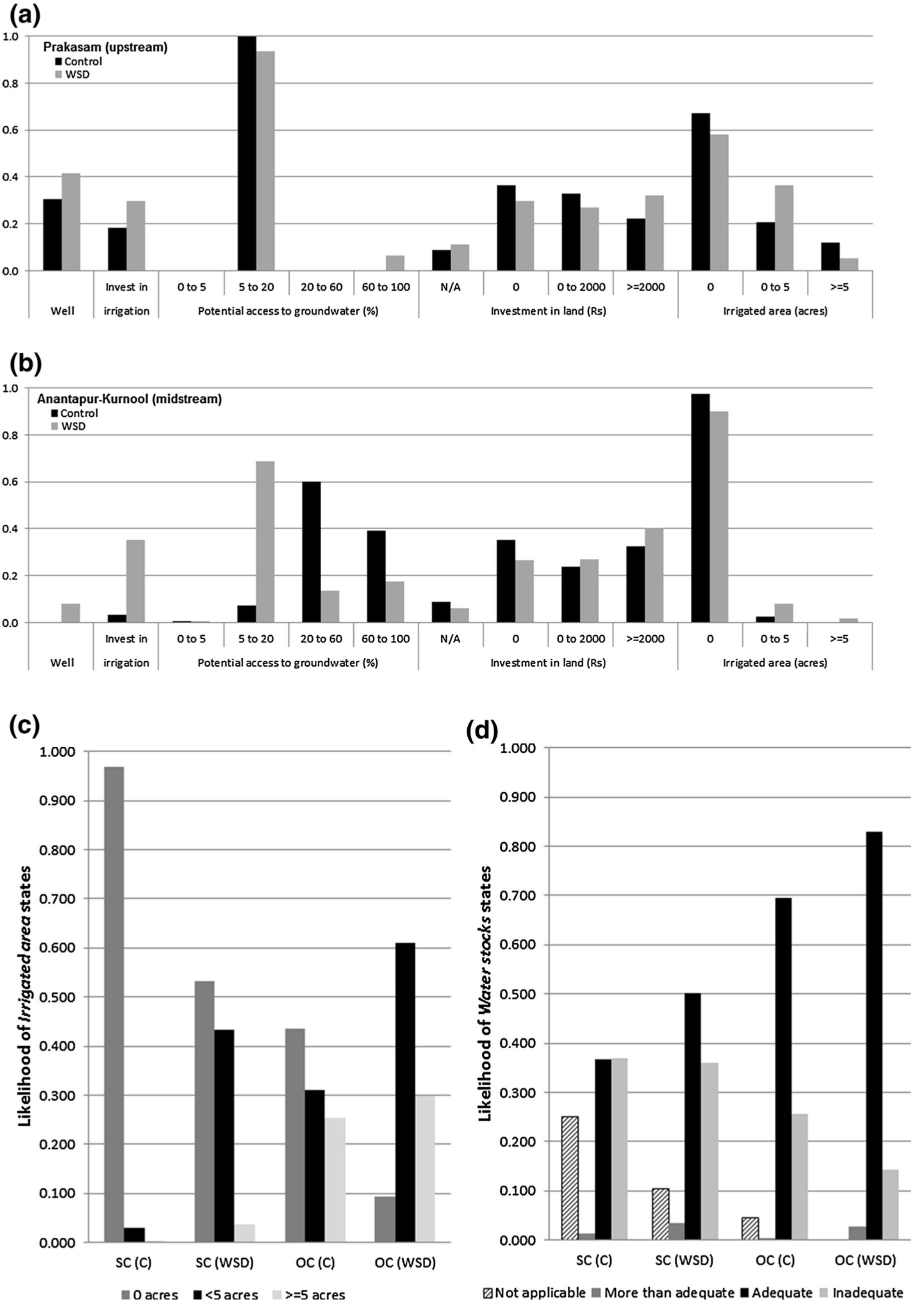

Fig. 6 Difference between land- and irrigation-related variables for control and WSD villages in the **a** Prakasam, **b** Anantapur–Kurnool hydrological units, and the likelihood of **c** irrigated area states and **d** adequacy of water stocks state for scheduled caste (SC) and other caste (OC) households in the WSD and control (C) villages in Prakasam

(28 %). The corresponding likelihood of adequate water stocks is 50 % in the WSD households compared with 37 % in the control households (Fig. 6d). The ‘other caste’ households are quite evenly split between small to marginal and medium to large farm size in both the control village (small to marginal = 50 %, medium to large = 45 %) and WSD village (small to marginal = 42 %, medium to large = 58 %). The majority of ‘other caste’ households in the WSD village invest in irrigation and own functional wells, 64 and 90 %, respectively, and most of the approximately 90 % who do irrigate do so on up to 5 acres of their land (61 %, Fig. 6c). In contrast, the likelihood of irrigation investment and functional well ownership in the corresponding control village is 39 and 55 %, respectively.

6 Household drought resilience and the five capitals

Among the survey households, when one type of capital is strong, the others are more likely to be strong. In particular, strong natural capital is associated with strength in financial and human capital, and households with strong natural capital have a higher likelihood of strong social capital and physical capital (Table 4). The relationship between natural capital and the other capitals may arise in a number of ways. Physical capital, for example, is defined in terms of ruminant ownership, a livelihood activity that is heavily dependent on land and common pool resources, and wells and agricultural tools which are owned almost exclusively by landed agricultural households. Similarly, households with greater financial capital tend to have characteristics which are associated with strong natural capital, such as larger areas of land and greater access to groundwater resources. The difference between the probability distributions of the *Resilience* variable obtained when each capital type is conditioned to ‘Weak’ or ‘Strong’ is shown in Fig. 7. For each capital, the likelihood of households having a drought resilience of three drought years increases substantially moving from ‘Weak’ to ‘Strong’ capital.

Analysis of the natural capital sub-model in the previous section suggested that WSD had relatively little influence on livelihood indicators (e.g. adequacy of water stocks) and the overall strength of natural capital despite increased access to groundwater infrastructure. This result is generally consistent across the other capital component BNs (not reported in this paper) and statistical analyses of the household survey data, performed concurrently with the BN development which identified little significant evidence of impacts of WSD on capital indicators (Reddy et al. 2014). These results contrast with the perceived impact of WSD reported in the raw data by survey respondents from households living within WSD implementation areas ($n = 430$). These households were asked how

Table 4 Relationship between the strength of natural capital and the likelihood of strong capital financial, human, physical and social capital

	Natural capital	
	Weak	Strong
Financial	55.8	59.8
Human	56.0	66.8
Physical	3.84	20.2
Social	10.5	20

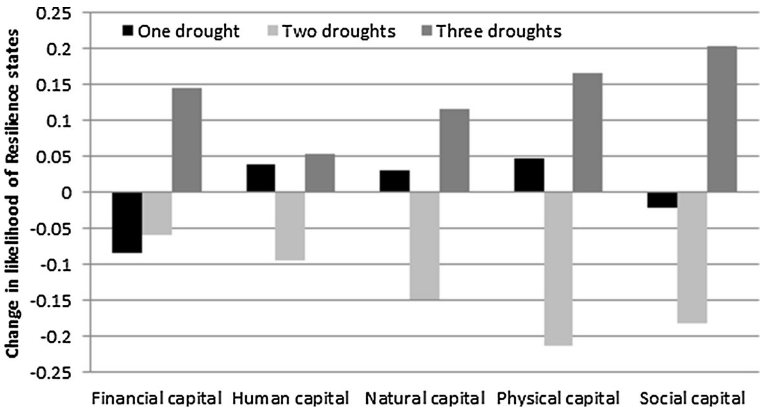

Fig. 7 Influence of the five capitals on household resilience to drought measured as the difference in likelihood of the Resilience variable states conditioned by each capital ('Strong'–'Weak')

many consecutive drought years they could survive given their current (2010–2011) situation and also how many drought years they could survive had their village not received WSD. Households overwhelmingly reported that WSD had increased their resilience to drought (90 % of households reported increased resilience). However, the perceived level of impact of WSD varied between households with more resilient households reporting a greater impact of WSD compared with less resilient households. Households with a resilience of three droughts most commonly (78 %) reported that they would have one to two years less resilience without WSD. In contrast, of the low resilience ('One drought') households, 57 % report that they would have up to 1 year less resilience without WSD, although 43 % report that there would be no difference from their current resilience to drought.

7 Discussion and conclusions

Ensuring that investments in watershed development achieve social and environmental objectives without adversely impacting communities outside of the programme implementation area is problematic although critically important. By adopting a meso-scale cluster approach to WSD design and implementation, the Government of India is taking measures to design interventions appropriate to the landscape and position within hydrological units and reduce negative externalities to downstream environments and communities. However, there is need for continued monitoring and development of rigorous analytical tools to assess the outcomes from IWMP programmes, perhaps more so given the increased implementation area. In this paper, we used the BN methodology to implement the sustainable livelihoods framework and represent factors influencing the strength of the five capitals (financial, human, natural, physical and social capital) and drought resilience of households. The BN sub-models form the basis of an integrated model being used to explore the response of hydrological, biophysical and socio-economic indicators to climate, land use and WSD scenarios.

Analysis of the natural capital model found little evidence demonstrating substantial differences in indicators of natural capital between WSD and control villages, beyond increased well ownership and irrigation. Unsurprisingly, the child variables of the *WSD* variable were typically more influenced by (or sensitive to) changes in the states of other parent variables, namely economic status or caste of the household, geographic location or climate. Households in the control villages reported a lower incidence of WSD village located in well ownership, irrigation and agricultural investment than households from the WSD village in a corresponding location. This trend is consistent across farming households from different castes although scheduled caste households, who are most likely to be small or marginal farmers, benefit less than 'other caste' households who are more likely to have larger farms. The greater access to wells and investment in irrigation for both hydrological units explains why more respondents report a higher 'adequacy' of water stocks for both the WSD villages, despite hydrogeological differences between the villages and the hydrological units. The potential access to groundwater is similar between the two upland villages in Prakasam in contrast with the Anantapur–Kurnool hydrological unit where access to groundwater is less reliable in the midstream WSD village than in the corresponding control village. The sustainability of this increased groundwater use is questionable; Sreedeevi et al. (2014) observed that groundwater levels in the study areas declined between 2005 and 2012 which they attributed to the allocation and use of groundwater in the watersheds exceeding recharge. Despite households being more likely to irrigate their land in the WSD villages, the impact on modelled natural capital and therefore drought resilience is not large. This is consistent with other analyses of the meso-scale survey data sets, performed concurrently with the BN development, which identified little statistically significant evidence of impacts of WSD on capital indicators (Reddy et al. 2014).

The BN methodology is well suited to implementation of the SL framework and, more generally, impact assessments. In this paper, BNs were readily able to utilise the household survey data that was collected using a retrospective non-random impact assessment. With the capacity to incorporate numerical and qualitative data, quantified stocks of capital assets (e.g. the area of irrigated land) could be related in the model to descriptive data such as the perceived quality of water stocks. The flexibility of the modelling approach ensures its value in supporting the broad range of impact assessment approaches from fully randomised control trials to participatory modelling or more qualitative approaches. Linking impact assessment data to systematic frameworks such as the SL framework using the BN methodology can foster system understanding by facilitating the exploration of interactions, influence and causality in the data. BNs are also a potentially valuable tool for planning phase of new intervention programmes whereby influence diagrams elicited through participatory modelling processes such as focus group discussions could be used to conceptualise how stakeholders (including community members, NGO's, GO's and/or researchers) think the system works and identify critical indicators to measure at prior to, during and post-implementation.

This study supports those of Calder et al. (2008b) and Kemp-Benedict et al. (2009) in demonstrating the possibility of BNs to be used, as one of a suite of tools, to support the effective assessment of a watershed interventions and their impact. However, some issues need to be addressed for the approach to be a practical tool that can be used by a range of government and non-government agencies to design and evaluate IWMP clusters at the meso-scale and generate learnings for future programmes. These include

- Establishing longitudinal biophysical and socio-economic datasets to support the analysis of impacts of interventions over time and space and the development of robust models.
- Developing consistent and intuitive methods for integrating qualitative and quantitative indicators into measures of vulnerability, resilience or wellbeing.
- Balancing the need for simple robust models against the value gained from representing causality.
- Achieving a balance between generic model structure based on the sustainable livelihoods framework and case study-specific model structures.
- Working with stakeholders responsible for designing, implementing and evaluating IWMP clusters to build capacity to develop and interpret BNs and improve the user-friendliness of the tools.

Many formal assessments of watershed interventions, including the meso-scale project (see Table 1), are undertaken retrospectively, sometimes years after implementation. Several issues have been identified with retrospective studies including issues of recollection, identifying contemporaneous events, changes in the type and level of impact over time and reliance on people's perceived impacts. Disentangling the level of impact of WSD interventions from contemporaneous events is very difficult to do if those events are not recorded or cannot be identified retrospectively (e.g. climate variability using climate records). This is an issue for all analytical tools, including BNs and the statistical methodologies typically applied to analyse impact assessment data, although can be controlled to a certain extent through careful design of the impact assessment methodology. In the meso-scale project, efforts were made to identify and control for such events. For example, available climate and hydrological datasets were used to identify the response of groundwater to climate variability. The study villages were selected from villages that had been part of the Andhra Pradesh Farmer Managed Groundwater Systems (APFMGS) project which was designed to promote sustainable management of groundwater by farmers through building their skills and knowledge (Source: http://www.fao.org/nr/water/projects_andra.html, Accessed 17th April 2011). This was done so that impacts of WSD were not obfuscated by the effects of the APFMGS programme. However, longitudinal studies offer a better chance of identifying contemporaneous events as researchers or implementing agencies can specifically design stakeholder engagement activities with affected communities to identify the various ways in which WSD or other concurrent interventions that may influence monitored indicators. Recording a core set of indicators before, during and after implementation of the programme during each survey phase should facilitate the representation of WSD impacts in the BN and the changes of these impacts over time. The opportunity for longitudinal studies should increase given that the IWMP explicitly requires monitoring, evaluation and learning systems to be put in place to evaluate and feed back into project planning and implementation.

With a long history (>30 years) of scientific studies and development programmes, there is decent understanding of the various livelihood indicators that can be used to assess impacts of watershed interventions, although some indicators can be difficult to quantify. For specific case studies, the potential indicators can be refined using focus group discussions and household surveys, as was done in the meso-scale project of which this research contributed to. Of greater difficulty is the task of translating the aggregated impacts of interventions on individual indicators, which may be inherently variable and uncertain, into a meaningful measure of change in household (or household type) vulnerability or resilience to shocks like drought. In this paper, and the larger project, we took a practical definition of resilience as the capacity of households to maintain their livelihood activities under consecutive drought years. This is a conceptually simple formulation that was highly relevant and understandable for the survey participants and also readily incorporated into the BN model described in this paper. However, summarising the capital livelihood indicators and linking them to the *Resilience* variable required the inclusion of 'capital strength' nodes. Without their addition, the CPT for the Resilience variable would have been prohibitively large and there would be insufficient cases (survey responses) to 'learn' the CPT. The process of adding aggregate nodes to the network reduces the combined size of CPTs in the network. Although this process can dilute the sensitivity of the final node(s) to the input nodes and increase the uncertainty propagated through the network (Chen and Pollino 2012), it is often a practical necessity in BN modelling.

The natural capital BN was evaluated using sensitivity tests to identify the strength of relationships between nodes and provide information on the robustness of the model to the amount of available data. These tests indicated that most of the CPTs in the natural capital BN that were learnt using the EM algorithm are reasonably robust, although variables relevant to irrigator households, which constitute about one third of households, are more susceptible to sample size. In the natural capital BN, the most impacted variable was *Irrigated area*, although the implications of sample size are likely to have more impact on the financial capital component model which includes variables describing crop types and productivity on irrigated land in addition to land area. The plausibility of model results were also assessed using scenario analysis within the project team and a limited set of stakeholders. The models, and the BN methodology more generally, would benefit from wider evaluation by WSD domain experts and local stakeholders, with particular attention to testing the network structure and assumptions used to define capital strength and household resilience to drought.

As they stand now, the BN outlined in this paper are intended for use by the research team to explore interactions and relationships in the resilience survey dataset. The focus of further development is to increase the flexibility within the models to represent WSD design and to develop a simplified model which incorporates the critical livelihood indicators (or stocks) affecting household resilience as identified using analysis of the detailed capital sub-models developed to date. The development of the BN into a user-accessible tool could aid the facilitation of group learning of watershed issues and implications of IWMP design and implementation by IWMP planners and practitioners.

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Appendix

See Table 5.

Table 5 Description and states of the variables in the natural capital sub-model

Name	Description	States
Household class variables		
Climate	Characterisation of rainfall years	Deficit, normal, excess
Economic category	The household farm size is used to represent economic status	Landless, small marginal (<5 acres), medium large (≥5 acres)
Hydrological unit	The hydrological unit within which the household's village is located	Anantapur Kurnool, Prakasam
Location	The location within the hydrological unit which the household's village is located	Downstream, midstream, upstream
Social category	The household caste is used to represent socio-economic status	Scheduled caste, scheduled tribe, backward caste, other caste
Watershed development	Whether or not the household's village has received watershed development	No, Yes
Factors affecting capital stock variables		
Access to CPR forests	Access to CPR forests	No, Yes
Direct CPR value (Rs)	Annual value (in rupees) obtained from direct use of CPR.	0, <2000, 2000 to 4000, >4000
Functioning well	Whether or not the household has a functioning well	No, Yes
Indirect value	Whether or not indirect value is obtained from CPR forests (e.g. mitigation against erosion)	No, Yes
Investment (Irrigation)	Annual investment in irrigation	No, Yes
Investment (Land)	whether or not households invest in land improvement	Not applicable, 0, 0 to 2000, ≥2000
Irrigated area (acres)	Area of irrigated land owned by a household (in acres) in 2010–11	0, 0–5, >5 acres
Potential access to groundwater (%)	The maximum percentage of bores at the village level that would be operational accessed under different climates	<5, 5 to 20, 20 to 65, >65
Rainfed area (acres)	Area of rainfed land owned by a household (in acres)	0, 0–5, 5–10, >10 acres
Value (Rs) of fodder	Annual value (in rupees) of fodder obtained from CPR forests	0, <3000, 3000–5000, >5000
Value (Rs) of fuel	Annual value (in rupees) of fuel obtained from CPR forests	0, <2000, 2000–4000, >4000
Water stocks	Self-assessed adequacy of water stocks.	Not applicable, More than adequate, Adequate, Inadequate

Table 5 continued

Name	Description	States
2010–2011 capital indicator		
Land area (acres)	Total area of land owned by a household (in acres) in 2010–11	0, 0–5, 5–10, >10 acres
Land quality	Self-assessed quality of land in 2010–11	Not applicable, Poor to Medium, Good
Value from non-timber	Whether or not direct value is gained from non-timber uses of CPR forests.	No, Yes
Resilience and capital strength variables		
Drought support (<Indicator>)	How many consecutive drought years the household's stocks of a particular indicator (e.g. income) would support household capacity to 'survive' (i.e. maintain their livelihood activities)	Not applicable, No drought, One drought, Two droughts, Three droughts
Capital strength	This variable is populated using the rule that capital is strong if any of the capital indicator stocks could last two or more consecutive drought years	Weak, Strong

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