Synthesis of household non-market values for the ecosystem services from a marine resource

Campbell. D[1], Chilton. S[2], Hutchinson, G[1]., Schuchert. P[3], Slater. M[3], Stead, S.M[3].

1 Gibson Institute for Land Food and Environment, Queens University Belfast, School of Biological Sciences, MBC, 92, Lisburn Road, Belfast BT9 7BL

2 Newcastle University Business School-Economics, , 5 Barrack Road Newcastle upon Tyne, Tyne and Wear, NE1 4SE

3 School of Biology, Newcastle University Ridley Building, Claremont Road, Newcastle Upon Tyne, Tyne and Wear, NE1 7RU

4 School of Marine Science & Technology, Newcastle University, Ridley Building, Claremont Road, Newcastle Upon Tyne, Tyne and Wear, NE1 7RU

Abstract

This paper describes a low cost method to synthesise a set of individual household WTP values to integrate into a marine policy decision support tool which takes account of the non-market values of ecosystem services when primary data is not available. Based on the principles of regression analysis, utilising empirical data from surveying Tanzanian fishery-dependent communities – 422 face-to-face interviews in 2010 - and using expert knowledge to assess the likely bounds on parameters, we generate a dataset of plausible values. This dataset was then inputted into a Bayesian Belief Network to demonstrate the impact of including and excluding such values in an assessment of the impact of implementing a Marine Protected Area (MPA) on a representative fishing community. The methodology tested supports the 'proof of concept' in the context of the scoping study in which it was applied. It remains an open question as to whether such an approach, subject to predetermined adaptations and improvements (such as sensitivity analysis using different functional forms or wider range of parameter values) would be applicable in a network developed for 'real world problem' policymaking. Nonetheless, we conclude the technique used is flexible, useful, low cost and has potential to be applied in decision-making to formulate policies that take account of non-use values, when no such data is available to the decision-maker.

1. Introduction

This paper describes development of a "proof of concept" for determining how people within a fishing community value ecosystem services obtained from marine resources, such as biodiversity, recreational fishing or health.. In many cases, policymakers do not have access to such data, as it has usually has not been collected in the past and they often lack the resources - both time and money - to commission a dedicated face-to-face stated preference study to address this gap and collect primary data. The research described herein applies a low cost and alternative method to deriving Willingness-To-Pay (WTP) data at the individual household level for subsequent use in a Bayesian Belief Network (BBN) model. The purpose of the exercise was to synthesise a dataset using expert knowledge informed both from understanding of an empirically-derived database with socio-economic information and from experience in developing countries. Carrying out such an exercise could also be used to evaluate whether carrying out a WTP field survey would in fact be useful in advance of implementation. For example, if it was indicated that including such values in the overall integrated assessment made very little difference, it may not be worth carrying one out. On the other hand, if policy outcomes appeared to change substantively when such values were included, it may be worth investing in a survey in order to acquire more accurate data. Methodological lessons drawn from the approach used to account for non-market values are described herein to share with the wider VNN network. This position paper supports the methodological development underpinning the NERC VNN project Interdisciplinary methods to build a socio-ecological decision-making tool to inform marine governance and policy[1].

The overall aim of the project was to develop a reproducible interdisciplinary framework to establish impacts of different policy and/or management decisions. The approach adopted involved building a dynamic decision model based on Bayesian principles (Spiegelhalter, Dawid et al. 1993; Levontin, Kulmala et al. 2011) to underpin the resulting decision support tool (Campbell *et al*., 2012). This incorporates marine indicators such as fish diversity and abundance and type of fishing, quantitative non-market monetary values for ecosystem services and demographic information such as income and number of dependents, and qualitative socio-economic and ecological measures of communities' perceptions of marine health and marine ecosystem exploitation. Stated preference techniques like contingent valuation and choice experiments to determine the WTP amount for non-use values in nature often do not include interaction variables to account for relationships across the different sectors of a community, meaning that they remain implicit in the analysis and hidden to the decision-maker. Thus one advantage of using the BBN approach is that this method extends traditional approaches by providing a means to visualise interaction variables in order to examine the influence assigned to the value, for example, nature conservation through taking account of an individuals' socio-economic and other demographic characteristics. Thus in our project we have extended the BBN model by explicit identification of key linkages, feedbacks and dependencies between different data types determined by the VNN team to allow the key relationships between them, to be captured within the underlying model. The resultant decision tool is capable of highlighting to policymakers and marine managers both the direct effects on marine health and sustainability, as well as previously hidden 'indirect' effects of a particular policy.

One potentially major indirect effect, identified by the VNN team and which is the focus of this paper, is the impact of marine management measures like Marine Protection Areas (MPAs) on individual household welfare. MPAs have been around a long time with the main aim often being to conserve nature and/or fish stocks (Roberts & Polunin 1993). MPAs are currently an increasingly popular choice for governments worldwide following

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recommendations for MPAs being written into international agreements such as the World Summit on Sustainable Development (WSSD) and Convention on Biodiversity (CBD) as part of their efforts towards conservation of marine resources. Notably, though, this occurs against a backdrop of little to no understanding of the impact this management measure has on individuals' who are socially and economically dependent on the marine resources that the MPA is designed to conserve. It is widely accepted that marine resource users like fishers and those affected in terms of their spatial behaviour at sea being constrained by the MPA, are unlikely to support the regulations imposed through marine policies that recommend MPAs. Thus Peterson and Stead (2011) recommend that prior to any implementation of marine spatial planning such as MPAs that good account is taken of the economic, social and environmental factors and used to influence the particular mode of operation, e.g. a complete ban on fishing – no take zone or multi-use zonation.

The impact on household welfare is more commonly known as the non-market value of a resource. Whilst there is a wide range of literature on the application of economic non-market valuation techniques, the challenge within this project was the integration of such values into the decision making tool, to establish whether this change of welfare at the household level, measured by the amount that households are willing to pay to obtain the ecosystem services resulting from an MPA, could be communicated to policymakers in such a way that its' impact could be seen on the three main components of the marine community represented in the model (marine health, economy, social well-being).

The remainder of the paper is as follows. We first briefly review the rationale for monetary valuation, followed by a description of the particular challenge and problem that we faced within the project, in terms of generating such values, with a view to deriving an, economically consistent exemplar household valuation dataset. We then present a description of our interdisciplinary methods to synthesise such data. Thereafter the results of a simulation exercise to demonstrate that the impact of such changes in welfare at the household level i.e. can be meaningfully captured and embedded in the overall policy impacts and communicated simply and quickly to decision-makers are described.

2. Non-Market Valuation

The overall aim of non-market valuation is to provide a proxy for the change in welfare or wellbeing (utility) resulting from an improvement (or deterioration) in the quality or quantity of a particular environmental "good", in our case marine ecosystem services such as fishing. Most usually this is captured by an individual's willingness to pay (WTP) for this change, although willingness to accept (WTA) measures can also be used. The underlying assumption is simply that if they have a value ("positive preference") for ecosystem services the individual or household would be prepared to give up some of their money to enjoy them; if not, they would not, preferring to spend their money on other things and, at least for some people, it is only the absence of a market that prevents them from expressing this preference ("market failure"). At this point, we note that, by definition, because such values are based on an individual perspective they incorporate shared social values only to the extent that these values are influenced by them. For example, there is no reason to suspect that an individual would give the same weight to beach recreation as society on the whole, although both may be interested in the preservation of such an opportunity. Given this, the VNN team decided that the appropriate place for these WTP values within the network would be in the Economy component along with the other economic, individual-based household characteristics. We now turn to the challenges we faced within this project in respect of including such values into our BBN decision tool, given that the datasets available to us did not contain WTP data - analogous to the problem confronting decision-makers described in the Introduction.

3. The Challenge

The VNN team focussed herein on addressing the economic challenge, that is, how to measure non-use values of marine ecosystem services at the individual household level.

Including the value of marine ecosystem services following implementation of an MPA, required a dataset at the household level. As such, conventional methods such as benefit transfer (Navrud and Ready, 2007) were not open to us. Benefit transfer is only appropriate for transferring aggregate (i.e. at the sample level) WTP values for a resource or its services derived from a valuation study to a similar resource at different sites opposed to values from individual households in one region to individual households in another. Thus, the major challenge we faced was that we did not have a WTP-based data set *per se* for our representative marine community in Tanzania (our main household data set derived from empirically collected data using 422 face-to-face household surveys). In the face of this, a two-stage process was agreed by the VNN team in which the economists should create an exemplar, economically consistent data set of the type that might be expected to result from a survey and that this (e.g. WTP and/or the size of parameters) should then be adjusted by the team to reflect the fact that the dataset was supposedly representative of that which would be collected from a fishing community in a developing country (in which the economists had no experience). This was considered an acceptable way to proceed within this study, given that the resulting 'estimates' would not be taken forward into a cost-benefit analysis), instead it would be used within the BBN to demonstrate the impact of including or excluding such data on the final (non-welfare based) policy outcomes across the three sectors of the community.

In essence, our synthesis exercise effectively allows us to assume that a stated preference survey has been carried out on our representative fishing community. We then derive a representative dataset of the type we think would be generated from such a survey.

4. Methods and Procedures: Valuation of ecosystem services

Available Dataset

The database that informed the valuation synthesis exercise consists of socioeconomic data and community perceptions' of marine environmental health collected in face-to-face interviews with 422 coastal village heads of households in four coastal villages in Tanzania (Unguja Ukuu, Ununio, Kunduchi and Buyuni) between March, and December 2010. The overall purpose of that particular study was to assess the extent to which fishery dependent communities are willing to consider aquaculture as an alternative or supplementary livelihood. This was done within the context of firstly determining the social and economic characteristics of the community members including dependency on ecosystems services like fishing in terms of income generation and food security. Study sites were identified based on their economic status, proximity to the coast and dependence on coastal income-generating activities. To summarise the communities are:

- Unguja Ukuu on the southern coast of Zanzibar, 31.6 km from its capital Stone Town (est. popn. 800 – 132 households).
- Ununio approximately 20 kilometres north of Dar-es-Salaam (est. popn. 1050 – 168 households).
- Kunduchi 15 km north of Dar-es-Salaam (est. popn. 1370 – 212 households).
- Buyuni 50 km south of Dar-es-Salaam, (est. popn. 1100 – 204 households).

Kunduchi and Ununio are ('diffuse') peri-urban fishing villages fringing Dar es Salaam, with encroachment of urban expansion on land area for agriculture and construction (Iaquinta and Drescher 2000). Buyuni is rural, and requires 3-4 hours travel to reach Dar es Salaam. Unguja Ukuu is rural and the only village included in the study with active (seaweed) aquaculture.

Villages were mapped using available satellite images as a reference and ground-proofing to create a full hand-drawn map of all roads and pathways and dwellings. The map was used to systematically sample (numbered) households within each community. The head of household in every third house (by numerical code) was interviewed in Unguja Ukuu. In Ununio, Kunduchi and Buyuni were mapped as above and the head of household of every second house was interviewed. Interviews were carried out at fish landing sites in Buyuni and Kunduchi with approximately 40 fishers and fishmongers in each village. Fishers' houses which had participated in interviews conducted at landing sites were excluded from household interviewing.

'Household' was defined as a unit of people that share a house (Sesabo and Tol 2005). Heads of households were interviewed where possible as decision-makers were considered to hold more detailed information about current livelihoods and associated costs of living. If the head of household was not available at the second visit, interviewers requested to interview an adult from the household fully informed about the household's full range of income-related activities and livelihoods.

Data collected from the interviews described respondents' marine resource dependence, perceptions of marine health and governing instruments, current economic status and employment Household income and household possessions and utilities, such as electricity, mobile phone and other physical assets such as house construction types (e.g. cement) and land and house ownership were recorded.

WTP Data Simulation

Empirical studies have shown that WTP is causally related to a number of individual characteristics (including socio-economic, demographic and attitudes). Thus, in order to obtain approximate WTP values for each of our sampled households, we specify a multiple regression model as follows

$$WTP = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_K x_K + \varepsilon \qquad (1)$$

where α is a constant, X_1 to X_K are the various individual characteristics that are assumed to affect WTP, the β terms are the coefficients that measure this effect, and ε is a random component.

In our case though, we cannot do this as we do not have individual household WTP data (LHS). What we do have, though, are a number of demographic and attitudinal data at the household level on the RHS. We developed the following method to infer the WTP that we might expect that individual household to generate, given its particular demographic characteristics. By assuming or imputing values for the β parameters at the sample level and applying them to the explanatory variables (X_1..X_K) to each of the households in our Tanzanian survey data, we can (after making a further assumption concerning the distribution of ε) approximate the RHS of eqn. (1). By so doing, we arrive at a synthesised WTP estimate for each of the sampled household in the dataset. We can further calibrate and check for biases introduced by the fact that this process is based on our experiences with datasets largely from valuation studies conducted in developed countries.

We stress that our motivation for this is to provide non-market values for the BBN model, which is one potential method to include such data in a policy evaluation. Whilst primary data is to be strongly preferred in real-world applications, in the absence of such information, the simulation of WTP means that we are able to demonstrate that non-market values (albeit simulated) can be integrated into the dynamic decision BBN model, thus highlighting its applicability and potential for helping policy decisions. We acknowledge that our approach and any assumptions that we make regarding the parameters may be considered arbitrary. Nevertheless, with careful consideration, we believe that plausible WTP estimates (i.e., which are somewhat compliant with those found in other studies) can be obtained using this approach. An additional, important point is that the BBN requires households to be classified in terms of their relative, rather than absolute WTP values. This removes some pressure in respect of accuracy, but there is still margin for error if the simulation exercise led to a distribution of households different to the one which would have occurred in a stated preference survey. This might well be the case since the classifications - into groups of households with low, middle and high WTP - are also conditional on the assumptions that we made . So while, we cannot state with absolute confidence that a simulated WTP estimate is accurate for any particular household, we believe that with appropriate assumptions the simulation exercise should provide a fairly good means for classifying households into groups. of. Although, we recognise that the threshold WTP values for. However, this is alleviated by the fact that these threshold levels are not of central interest in our experimental

BBN model. Notwithstanding this, we tested Aa number of simulation scenarios under a variety of assumptions and we settled on the one that seemed, in our opinion, the most plausible.

Ultimately, after experimenting with various functional forms it was decided that the following expression could be used to approximate WTP for household *n*:

$$\widehat{WTP}_n \cong \alpha + \beta_1 MSL_n + \beta_2 HH\_Inc_n + \beta_3 Age_n + \beta_4 {Age_n}^2 + \beta_5 Male_n + \beta_6 Educ_n + \beta_7 N\_Dep_n + \beta_8 Less\_FishDep\_HH_n + \varepsilon_n \quad (2)$$

The final model comprises of seven independent household specific variables. The first of these is material style of life (MSL) which is a numerical estimate based on possession of certain material possessions such as a concrete house, tin roof, electricity etc. In line with the majority of valuation studies we include household income (per month in USD), which is labelled as HH_Inc IN (2), as an explanatory variable. We also include age (in years) of the household head (person who makes decisions about finances or who is knowledgeable about how finances are managed in the household). Following intuition and evidence from the safety valuation literature (REF)our, we specify that this has a quadratic affect on WTP i.e. low WTP at younger and older ages with WTP peaking in midlife. Similar, we allow for further characteristics of the head of household to have a bearing on WTP. Specifically, we facilitate gender influences with a male dummy variable, labelled Male, and accommodate the role of education (in years), labelled Educ. The number of dependants, denoted using N_Dep, within the household is also included in the WTP expression (2). Finally, when simulating the WTP estimates we include a dummy variable which takes the value of 1 for households that are relatively less dependent on fishing (i.e., where less than half of the household income is from fishing) and a value of 0 otherwise. We label this variable as Less_FishDep_HH.

Our final step in simulating the WTP estimates was to determine the values for the α constant and for each of the β coefficients as well as decide on an appropriate distribution for the random term ε. Given that our overall objective of this simulation is to identify respondents according to their relative rank in respect of their household income level (e.g. High, Medium, Low), we can set α=0 (i.e., since it is added to all households its value does not affect the relative rank). Determining the β coefficients, however, is not so straightforward. Nevertheless, we at least have priori expectations of the sign of the coefficients and of their relative magnitude. For the coefficient associated with MSL, we specify β_1>0 (since it is believed that households with a higher standard of living will also have a higher WTP). We make the further assumption that a one-unit increase in the MSL index increases WTP by USD 0.11 per month. Income typically has a positive influence on WTP. In our simulation we specify β_2=0.0045, meaning that the ceteris paribus effect[2] of income is a USD45 increase in monthly WTP for every $1000 increase in monthly household income. The relation of age on WTP is assumed to be quadratic and, therefore, the change in WTP with respect to the change in income is β_3+2 β_4Age. We set β_3=0.000015 and β_4=0.0001 so that, while age has a

[2] The effect of income, holding other variables constant.

positive relationship, it has a very minor influence (e.g., other things being equal, a head of household aged 70 years is assumed to be only willing to pay USD0.01 more per month compared to a head of household aged 20). We expect head of households who are male to have a lower WTP, of the magnitude of USD0.075 per month. In simulating the WTP estimates we specify the ceteris paribus effect of each additional year of education at USD0.007 per month. To recognise the fact that WTP is latent (i.e., not observed), it is important include a random component in the WTP calculation. For this we assume that ε=0.6v, where $v \sim \mathrm{U}[-1,1]$.

By inserting our assumed values of α, β and ε into Equation (2) we can arrive at an approximate WTP for each of our sampled households. The resulting distribution from these calculations are presented in Figure X. From this we see that our simulated WTP estimates range between –USD0.75 and USD7.00 per month and there is a central tendency around USD1.50. Interestingly, when we compare these computed WTP value against the household income, they are generally within the 1% of annual household income, which adds some validity. As stated earlier, however, the actual value of WTP retrieved from this simulation exercise is not of central interest. Our main attention is given to the relative ranking of households in terms of their WTP. We, therefore, classify households into three groups of approximately the same size on the basis of their WTP. This is also displayed in Figure X. These groupings are then used within the BBN model.

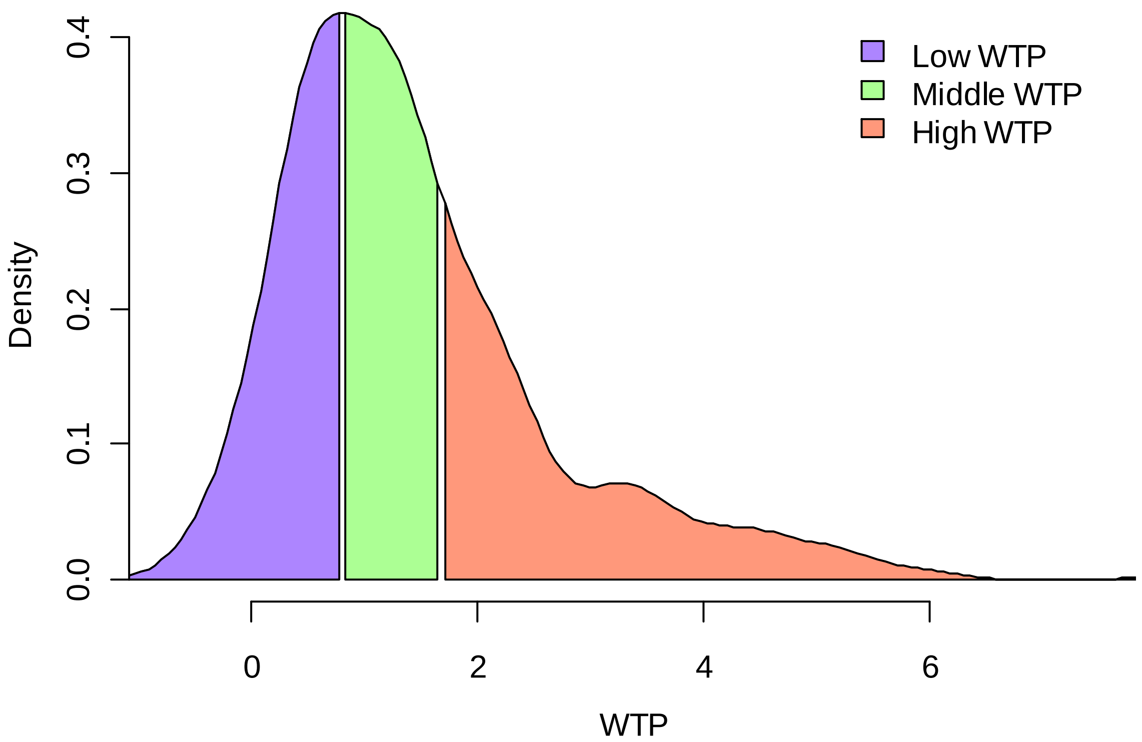


Figure X: Distribution of simulated WTP

5. Incorporation of Non-Market Values into the BBN

The full BBN model is reported in (Campbell *et al*. 2012). Fig. 1 contains a subset of that network specifically related to the WTP data, in the sense that it reflects the main direct and indirect variables (nodes) that it was deemed reasonable to assume would influence WTP in a marine community[3]. The WTP node then links directly to the headline indicator for the Economy component, that of (total) **economic output** for that community (comprising use, or market values and non-market values) in the BBN. It is also possible, if selected, to create similar networks customised to specific income groups, as illustrated in Appendix 1, although we focus herein on the network that includes all three income groups here.

Table 1 presents the results of running the BBN[4] under four different scenarios.

Baseline: No information about the community is available, i.e. all possible states of each input node have got the same probability.

Poor State of Reefs: As baseline, but the current fish stock is low, habitat type is a reef

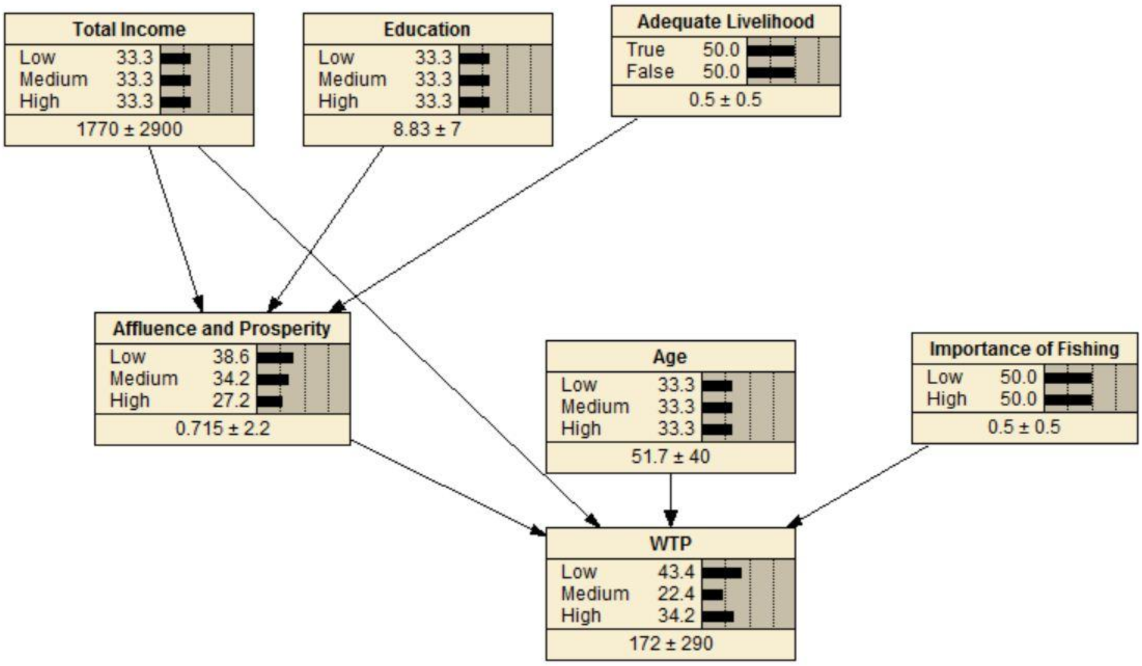
Heavy Fishing: As above, but trawling is used in the community, there is a high demand for fish, the community has a dense population and 80% of the fishers own their own boats.

Small Scale Fishing: Medium local population only using hook-and-line fishing and traps, fish stock at current time is average.

Figure 1 – title and legend should be underneath figure

[3] Netica software created the graphs in Fig. 1 and Appendix 1. The network was specified via a generalised linear model (GLM)from the synthesised WTP data.

[4] Note that, due to some limitations in netica, these simulations were run using genie software, and, because of (different) limitations in that program, the linkages within the model could not be specified via a GLM. Instead, educated assumptions were made about the directional impact (increase or decrease WTP). A more detailed assessment of the strengths and weaknesses of available software is contained in (REF PROCESS PAPER) and will not be expanded on here.



The probabilities for each level of economic output value (Low, Medium, High[5]), expressed in percentage terms, are displayed under the four scenarios, with and without an MPA and excluding and including non-market values (WTP). So, for example, , if we were considering a community with a poor ecosystem state without taking into account non-market values, the likelihood that that economic output value is, relatively speaking, low 0.56 (or 56%), that it is medium is 0.35 (35%) and, finally, high is 0.08 (8%).

On the most general level, it can be observed that the distribution of likely output levels changes when we both implement an MPA and, further, when we include non-market values. Considering the situation in which an MPA is implemented, it is shown that this can make a difference to the potential levels of economic output value. For example, in the Poor Ecosystem State, the likelihood of Low, Medium and High levels of economic output value change from 56%, 53% and 8% respectively to 60%, 32% and 8%, while in the 'Subsistence Only' scenario likelihoods change from 36%, 43%, 21% to 39%, 39%, 23%. Including non-market values can induce further changes. Thus, in the case of our 'Subsistence Only' scenario the likelihood that economic output value would be Low falls from 53% to 39%, Medium increases from 36% to 39% while High increases from 11% to 23%. This reflects the fact that including non-market values in the value of economic output offsets the fall in value (revenues) from reduced fishing under an MPA, at least at an aggregate, societal level. Meanwhile, under the Heavy Fishing scenario it makes no difference, in that the likelihood of each level of economic output value remains the same in both cases (60%, 32%, 8%), as

[5] Although we have chosen to describe our indicator variable state with three categories, this is flexible and could be changed in accord with policymaker preference e.g. Improve, Deteriorate.

might be expected (such ecosystem are likely to be severely degrade already and would therefore provide little, if any, non-market ecosystem services, implying a low or zero WTP).

Table 1 Results from the BBN (Implementation of an MPA and Inclusion of Non-Market Values)

MPA		NO		YES	
Scenario	State	Economy (%)	Without WTP (%)	Economy (%)	Without WTP (%)
Baseline	Low	40	47	41	55
	Medium	42	41	38	35
	High	18	7	21	11
Poor State of Reefs	Low	56	36	60	60
	Medium	35	38	32	32
	High	8	5	8	8
Heavy Fishing	Low	56	57	60	60
	Medium	36	35	32	32
	High	8	8	8	8
Small Scale Fishing	Low	36	46	39	53
	Medium	43	41	39	36
	High	21	13	23	11

Observe that we are careful to simply report these changes How policymakers responds to such changes, whether they perceive them to be 'significant'[6] or not, and, importantly, how they trade them off against simultaneous changes in the other headline indicators in the BBN (Social Wellbeing and Marine Health) is a value judgement on their part. The point here is that using the BBN we can demonstrate and communicate the overall impact of a policy on the value of economic output when non-market values are taken account of.

6. Concluding Comments

This paper has reported how the VNN team dealt with the challenge of deriving a WTP data set at the level of the individual household for use in a BBN model to take into account non-market values. As noted, given that final policy outcomes are not described in terms of monetary welfare gains and losses, it was agreed that a synthesised dataset of plausible values would suffice for our purposes i.e. demonstrating the impact of including such values on our final headline indicator, in this case economic output value, given that the individual level data required was not available and, as

[6] In the second Full Team Meeting, to which policymakers participated they remarked that they would expect any changes form a particular policy to be fairly small at a societal level. Indeed, if they were "large" this would be a cause for concern.

discussed, conventional methods (e.g. benefit transfer) were not suitable. It is an open question as to whether such a procedure, subject to certain adaptations and improvements (such as sensitivity analysis using different functional forms or wider range of parameter values) would be acceptable in a network developed for real policymaking, but for our "proof of concept" requirements it has proved flexible, useful and low cost.

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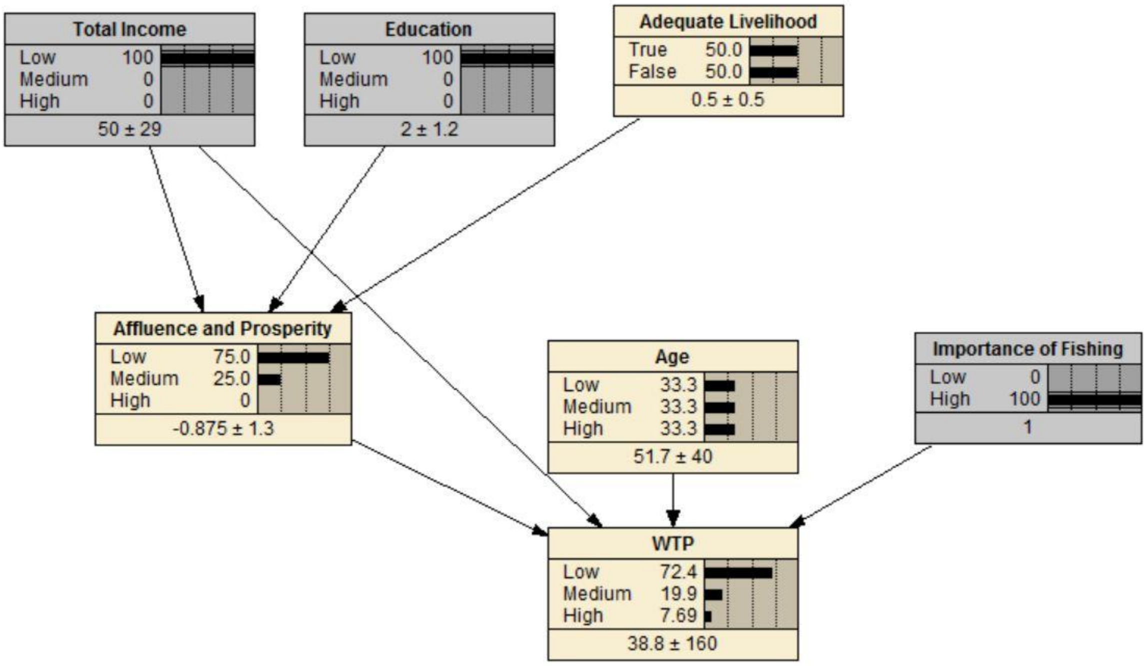
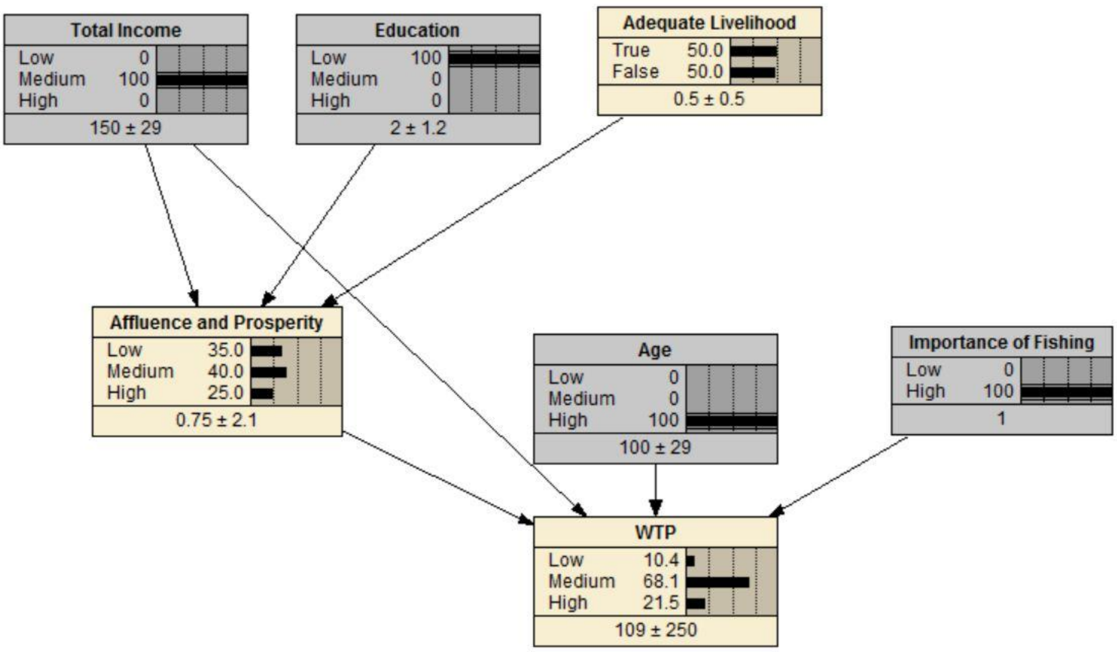
Appendix 1

(i) ***Low Income, Low Education Level Households***



(ii) ***Medium Income, Elderly Households***



(iii) ***High Income, Highly Educated Young Households***