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Economics of environmental effects on health: A methodological review based on epidemiological information

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ABSTRACT

Economic analysis of environmental effects on health in terms of use and non-use value opens analytical avenues of evaluating criteria, further beyond the results of epidemiological analysis. From the methodological review of the papers, it is inferred that scanty literatures are partially devoted to yield some use value or facts from epidemiology to economic impact evaluation method, basically taking either temperature or humidity and climate change. Based on the methodological issues available in the literatures, this paper critically explored a state-of-the-art-review of methodology with their gaps for the establishment of a new model methodology, incorporating a strong economic valuation procedure for use and non-use values of environmental health effects which creates many rooms for innovative economic evaluation methods beyond the epidemiological results. The demonstration of a new model methodology is able to moisturize the thrust of researchers in quest of a complete methodology for the economic analysis of effects of environmental change on human health.

1. Introduction

Observing environmental health issues through the eyes of microeconomics in terms of diseases burden caused by environmental degradations at household level is a daunting task because of uncertainty present in seasonality effect and non-use value (Moon et al., 2013) of environmental goods and services over the year. However, methods applied in empirical research to know environmental impacts on human health are common with technical methods rather than economic aspects, which only allow to evaluate the use value of the effects (Walker and Ben-Akiva, 2002). Methodological concerns in evaluating non-use value of environmental degradation directly linking with human health through the perspective of inter-temporal utility change is yet to be well organized in the scientific community, hence this study has explored this concern considering the dichotomous response from demand side.

Persuaded but acrimonious fact is that the effects of environmental change may have significant impacts on several thematic areas such as health, agriculture, nutrition, inequality, life expectancy, impoverishment etc. which can be calculated by econometric tools like different forms of regressions to investigate the facts of cause and effect relationship using community-based datasets. A development of environment-household poverty trap model seems associated with nutritional status at household and much effective to address the complexity of world poverty reduction targets (Barbier, 2010). An association between environmental degradation and economic prosperity can be identified from structural equation modeling specified with partial least squares (Lu, 2014). This modeling minimizes the problems with measurement scales, sample size, and residual distributions, true independence of the variables, data structural problems such as skewed distributions and omission of regressors etc. With the major concern of this study to review the economic valuation methods for environmental health issues, the summary of methodological review portion of this study as demonstrated in Fig. 1 describing evaluation techniques is considered a base for the model methodology formulation.

Importantly, the use value of health commodity under estimate the exact economic value of health status changed, probably induced by environmental change, that may misguide in results of effectiveness and monetary measures; hence the addition of non-use value of community health status is an alternative to reflect the total gain of household. Effectiveness of an intervention mainly concerns with long term impacts of health, but economic evaluation fails to monetize the exact effects with pros and cons. For example, odds ratio can capture partial effects in physical terms in one side mainly through the service provider's perspective. While monetary measures, for instance, economic cost

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benefit analysis examines use and non-use value of health programs, basically through the demand side, which motivates the consumers to invest on the programs for their own welfare.

Concerning in methods in the existing literatures, a review of methodological aspect of available literature as reviewed in a recent paper (Paudel, 2018) claims that most of the scientific studies of 1990s are devoted on the descriptive analysis as the method for climate-health relationship establishment (McMichael and Haines, 1997; Sutherst, 1998). Similarly, the studies during 2000s seemed slightly tilted towards the econometric analysis by using Poissons regression model (Parham and Michael, 2010), simulation studies (Hunter, 2003), downscaling approach (Patz et al., 2005), climate suitability model and dynamic process based mathematical model (McMichael et al., 2006; Reiter, 2008) which are predominantly used to assess the vulnerability of climate change on diseases. And the recent papers from 2011 to the date are devoted to explore some new methods such as cox regression (Imai et al., 2015; Weichenthal et al., 2017) and odds ratio combined with several analytical designs incorporating sensitivity analysis in variables variability.

Moreover, as per a recent review paper (Paudel, 2018), advanced ecological niche modeling, entomological vector surveillance, early warning system and country-wise spatial and temporal scales economic evaluation based studies including socioeconomic factors are recommended for future studies. Likewise, Monte Carlo version of the fisher exact test, retrospective time series analysis, medio-geographic analysis, negative binomial regression model, climate based ordinary-differential-equation model etc. are the major statistical and econometric methods followed by most of the papers seeking relationship of environmental components with diseases.

The major concern of these methods seemed either to evaluate the environment issues or health issues, or partially to see the epidemiological linkages of climate with disease. Partial information on environment or health issues includes one way method just to reach the objectives, but informs incomplete methodology inference for researchers of environmental health. Accordingly, the researchers might not potentially claim about methodological robustness with high confidentiality if they follow partial analytical methods. Consequently, the environmental health being as a procedure for evaluating aggregate environmental effect on health should incorporate a complete idea with epidemiological and economic analysis in a single study that aggravates methodological procedure ensuring the robustness of the study with desirable outcomes.

At the same time, unfortunately, no single study is found with a complete methodology with economic analysis, beyond the epidemiological studies, of environment-health relationship. Considering this methodological gap in the existing literatures, evaluation of use and non-use value in health and environmental issues through econometric tools with thorough review and discussion can be a useful contribution at this moment. Therefore, the major objective of this paper is to explore methodological gaps from thorough methodological review and demonstration of a new model methodology regarding the economic analysis of environmental health to add in the existing poorly managed methodological development among the literatures. For this, epidemiological impact and economic impact of environmental changes are first broadly separated and thoroughly reviewed covering the literature from 1990 to 2018. Subsequently, a model methodology is thoroughly presented with econometric methodological theories.

2. Epidemiological impact analysis of environmental changes

Epidemiological studies have predominantly conducted with either experimental or quasi-experimental or observational studies to observe the impact and effectiveness analysis. However, very few studies examining consequences of environmental changes on health follows experimental and quasi-experimental methods, for example clinical trial, because the researcher can control over the association of various extraneous factors in the new health outcomes. But, most often, environmental changes affecting the human health are not under control of investigator, so with the absence of randomization, together with the inability to control the exposure of interest and related factors makes this kind of study less precise for establishing a causal relationship between a risk factors and health outcomes.

Majority of the environmental health studies employ the population based observational studies. Methods in epidemiological studies are basically differentiated and featured with some major issues: sample selection from population, exposure measurement, dealing with other

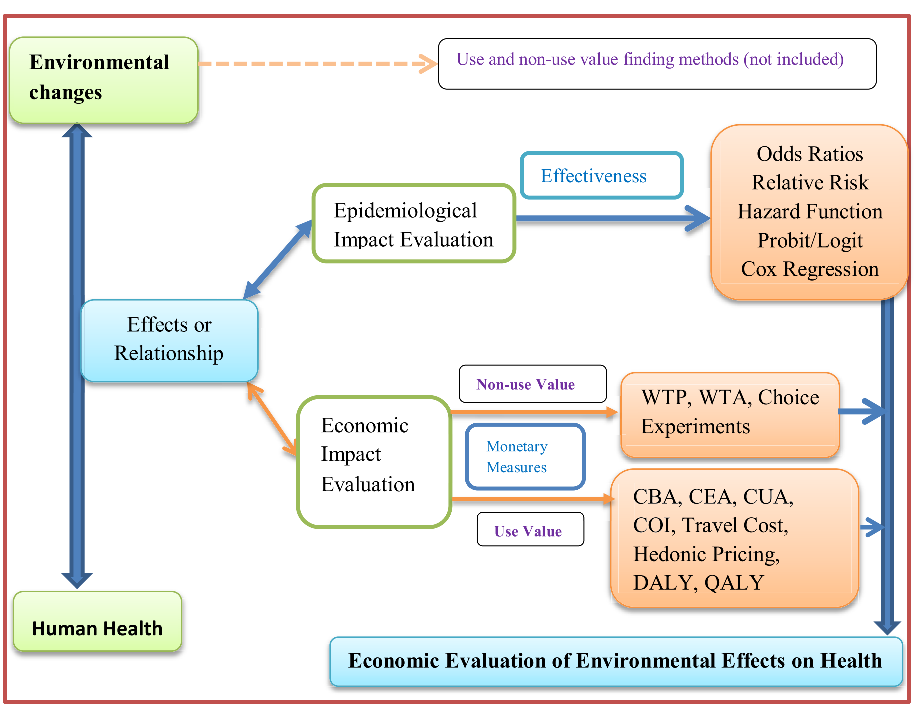

Fig. 1. Conceptual framework for economic evaluation of environmental effects on health.

relevant factors, involvement of matching, coding risk factors in regression model, estimating damage functions, assumptions for the involvement of choices, reporting uncertainty, potential issues to influence the accuracy of result and causality demonstrations.

Disease prevalence and incidence both represent proportions of a population determined to be diseased at certain times. Prevalence and incidence proportions are different with the calculation of population at risk and new cases during the interval of time. The simplest and careful use of these measures of disease occurrence depends on their comparison across study subgroups that have experienced different levels of exposure caused by environmental changes. For example, if causality is of prime concern, it is almost always necessary to use incidence, rather than prevalence, as a measure of disease occurrence. On the other side, a careful choice of an appropriate interval is mandatory when incidence proportions will be calculated because if the time interval underlying the definition of an incidence proportion is long, an incidence proportion may be less useful if, for some groups, cases tend to occur much earlier in the interval than for other groups. To identify the incidence rate; hazard function and survival functions are helpful to quantify the risk of diseases caused by natural agents, where the use of Poisson regression models is an attractive approach to rate data.

For the presence of multiple source of randomness in epidemiological investigations, a key step in quantifying the uncertainty inherent in such studies can be conditional or estimated probability and several complex sampling techniques. In more complex sampling schemes, the basic philosophy for constructing interval estimates remains the same, but expressions for both proportion estimators and their associated sampling variability must be modified to incorporate relevant sampling properties, confidence interval and estimation of sampling design. Some major methodological concerns harnessing in available literature are explained henceforth.

2.1. Odds ratio and relative risk

Most conjoint in health system analysis but with dynamic explanatory analytical tool, odds ratio (OR) explains the ratios between probability and non-probability of the events. It establishes the association between binary variables or multiple variables reflecting the magnitude of an association with high confidentiality, however the robustness of the association relies on the interactions (examines single summary value is useful or not), confounding influence and independence in the variables used (see Selven, 2011). Relative risk (RR) is useful to observe the probability ratios with and without risk factors. For rare disease like cancer, OR and RR are almost with same value because of similarity in mathematical treatment of different magnitude in numerical data in the comparison of likelihoods of the disease between individuals with and without the risk factor.

The retrospective and case-control study need a comparison of the likelihood of the risk factor between individuals with and without the disease; but for prospective and cross-sectional study, the comparison of the likelihood of the disease among individuals with and without the risk factor reflects the precise value. Though, being both RR and OR relative measures of risk but not symmetric in the role of the two factors disease outcomes (D) and exposures (E), the RR and symmetric in role of OR stand basis of a multiplicative model for risk analysis in the sense that, to obtain the risk of disease for an exposed individual. If $RR > 1$; there is a greater risk or probability of D when exposed *(E)* than when unexposed the reverse is true at $RR < 1$. Similarly, $OR>1$ when there is a greater risk of D with E present, and $OR<1$ when there is a lower risk of D if E is present. Like *RR, OR* must be nonnegative, but unlike *RR, OR* has no upper limit (see (Nicholas, 2004)).

Using this theoretical concept, a study based in South Korea explained the climate-disease burden relationship by the use of odds ratio and disability adjusted life years using secondary data (Yoon et al., 2014). Another population based case-control study conducted in France observed a relationship between occupational exposure to chlorinated solvents and head and neck cancer risks through the estimation of odds ratio by running an unconditional logistic regression (Carton et al., 2017). Similarly, odds ratio also yields the decisive estimate when the comparison of best regression models, for example, comparison among Bayesian additive regression tree, Bayesian kernel machine regression and Super Learner in the examination of environment risk scores associating with numerous health endpoints (Park et al., 2017). A cross-section study in Ethiopia (Wielsøe et al., 2017), another time series study finding the relation between asthma and climatic indices (Soneja et al., 2016) and a case-control study of Greenland (Wielsøe et al., 2017) have interestingly demonstrated the use of odd ratios in the explanation of environment and epidemiological associations. However, odds ratio provides absurd results when disease and exposures are asymmetry in the roles.

Regarding relative risk, a Russian study used risk modeling methodology (population attributable risk) to calculate relative risk of disease burden due to alcohol consumption, compared to other countries (Shield and Rehm, 2015). Another study of Colombia used Integrated Nested Laplace Approximation technique to estimate relative risk of Dengue incidence (Adin et al., 2018). The structural uncertainty in environmental factors causing health consequences can be plausibly treated with damage functions by choosing the parameters of a parsimonious analytically-tractable functional form, either in prototype multiplicative or additive form of specifications (Weitzman, 2010). Damage function seems better to identify the social cost of environmental change including socioeconomic factors, especially, in the marginal damage evaluation of climatic hazard. The economic growth attributing to the environmental pressure can be analyzed by damage functions (Munasinghe, 1999). Though this function is appropriate in economic analysis of environmental change, its specification when it is used is quite complex in the conversion of reduced form, in terms of quantitative aspect and mostly omissions of the scale of damages (Stern, 2013).

Cochrane-Mantel-Haenszel Method and Woolf's Method are the alternative methods for averaging odds ratio estimates across strata of population that works surprisingly well regardless of the sample sizes and marginal balances in the stratum-specific 2×2 tables (see Nicholas, 2001). The Cochrane-Mantel-Haenszel Method, an advanced and modified form of chi-squared test, simply constructs a test statistics by comparing observed and expected values, and analyzed considering the independence of exposures with disease risks; as followed by a recent meta-analysis based review study (Pradipta et al., 2018) seeking the association of risk factors of tuberculosis. However, these methods being absolutely new and advanced, limited studies are found applied these methods in the research.

2.2. Hazard function, relative hazard, excess risk and attributable risk

First, hazard function (graph explaining disease incidence rate over a period of time) is obtained by dividing cumulative incidence proportion by survival function.

$$h(t) = \frac{dI(t)}{dt} \Big/ (1 - I(t))$$

here, h(t) is hazard function at time interval t, dI(t)/dt is cumulative incidence proportion and (1-I(t)) is survival function where I(t) is cumulative disease incidence proportion. The plot of survival and hazard function seems reverse. But the plot of hazard function is useful in the comparison, for instance, mortality risk in first year of life and after 60 years of life. As the interpretator for age-specific incident function (Park et al., 2017) and risk changes over exposure level (WHO, 2009), hazard function seems useful for the epidemiological studies. Prentice and Thompson (1984) used hazard function modeling to investigate the dose-response analysis of cancer hazard.

Relative hazard (RH) explains the ratio of hazards with and without risk exposures. If $h_E(t)$ and $h_{\overline{E}}(t)$ the hazard functions over the interval [0, t] for the exposed (E) and unexposed ($\overline{E}$), respectively, then the relative hazard functions for the two groups by $h_E(t)$ and $h_{\overline{E}}(t)$ at time t is, $RH(t) = \frac{h_E(t)}{h_{\overline{E}}(t)}$. If disease incidence without exposure is very small over the interval of time; then OR, RR and RH yield the same value. Jarup (2004) and Oiamo (2014) used relative hazard modeling to analyze the chemical exposure and human disease risk differences among different geographical areas. Similarly, another study has recently explored the increasing risks of Lyme diseases due to biodiversity change using the concept of relative hazard (McClure and Diuk-Wasser, 2018).

Excess Risk (ER) is the absolute measure of risk differences between the exposed and unexposed disease incidence and is calculated by $ER = P(D|E) - P(D|\overline{E})$.

Here, $P(D|E)$ and $P(D|\overline{E})$ are the probability of risk of disease with exposed and without exposed, respectively. The value of ER lies between 1 and -1, as ER $>$ 0 means high disease risk and vice-versa. This concept is carefully used to assess the level of livestock disease risks due to antimicrobial use among the east African Agropastoralists (Ahmed et al., 2018). Another Canadian study explored excess of lung cancer risk due to the exposure in industries and occupational environment using excess risk modeling (Jung et al., 2018).

Attributable Risk (AR) is a ratio between a deduction of disease cases without exposed from the total disease cases and total disease cases. Symbolically, $AR = \frac{P(D) - P(D|\overline{E})}{P(D)}$

Attributable risk is more explanatory than RR and OR because it further examines after once the value is measured by RR and OR. The value of AR lies between 0 and 1. Interestingly, attributable risk conceptually presumes an unadulterated intervention that can exterminate exposure to E. A fact that a single paper fully devoted to explore the attributable risk and excessive risk is hard to find. None of the scientific study is found reaching to finding the attributable risk analysis or modeling for environmental health. However, a study by Shield and Rehm (2015) has modeled population attributable risk concept in the analysis of disease risk associated with alcohol consumption.

2.3. Case-cohort studies and case-control studies

Within case-control studies, an analysis is generally made between two subgroups of the population, one group of cases with treatment (D) and another control ($\overline{D}$) with same level of (environmental) exposure E, leading to the odds ratio for the estimation of explanatory variables. A study (Knibbs and Sly, 2014) carried out in Australia inferred the health and environmental risk factors using case-control study. Other some studies exploring the effects of climate on human health have employed case-control study as the supplementary tool for the inference drawn (Burbank et al., 2017; Oiamo, 2014; WHO, 2009). However, this study design is not applicable for the rare population because of the heterogeneity in individual cases and individual exposures. Moreover, cohort study together with several study designs for instance prospective, retrospective etc., seems most common in use in the evaluation of health issues concerning with environmental factors. Some recent literatures used this design to evaluate the association of ambient pollutants with respiratory disease (Tin et al., 2016; Weichenthal et al., 2017), whereas a study (Pollock et al., 2017) based on developed country have observed the air pollution effects on asthma and other respiratory diseases through perspective cohort study. Besides, a retrospective study is employed in a study (Gallagher et al., 2017) to exploring associations between prenatal solvent exposures and teenage drug and alcohol use.

Case-control method stands stronger to release the potential results over cohort study to analyze the association between occupational exposure to contaminated underground water and diseases incidence risk, since cohort study lacks the control and proper adjustment of confounders and accumulates the partial probability, which might release inaccurate unconditional logit results or odd ratio (common practice in epidemiologic studies) (Carton et al., 2017). Rather, retrospective cohort study is more informative in use to evaluate the impact of prenatal and early childhood exposure to contaminated drinking water on the occurrence of risk-taking behaviors (Gallagher et al., 2017) when there is adequacy of long term perspective information. The employment of some econometric tools such as poisson, negative binomial and logistic regression in the examination of the prevalence of the animal diseases from wastewater (Elahi et al., 2017) including environmental, behavioral and economic factors can be another innovation on research methods over present studies. Population based studies seems more relevant to identify the association between environmental exposure and human health, however some particular case being dependent upon laboratory analysis.

2.4. Regression models

Linear regression is simple and common in use, is looked as $P_x = P(D|X = x) = a + bx$, explaining exposure level $X = x$ changes with linear change in risks, and a and b as parameter where b changes with the change in exposures level. Though this model is useful for examining the excess risk with the increase in exposure by unit, the estimation of OR and RR linked with case-control structural databases for binary outcomes are impossible from its use. Pretty advanced and known as alternative for linear model, i.e log linear model with log risks and exposures is useful when RR is first measure of association but not effective for traditional case-control datasets.

2.4.1. Probit model

Probit model is applied when researcher needs no negative and risks greater than 1, with taking the values of binary risk between 0 and 1, specified as, $P_x = P(D|X = x) = \varphi(a + bx)$, here value of b responds the change in risk as b $>$ 0 means greater the risk of exposure and vice-versa. Among recent advanced research methods, a recent study (Paudel, 2018) potentially established the environment and disease relationship using the model. Similarly, another study (Pant, 2008) with the aim of exploring the relation of air pollution variables to chronic bronchitis and asthma employed this method as the corrective measure for the problem of endogeneity among variables.

2.4.2. Logistic regression model

Simple logistic regression model mainly assumes that the log odds of disease risk D changes linearly with changes in predictor X, can be presented as, $Log\left(\frac{P_x}{1-P_x}\right) = Log(oddsforD|X = x) = a + bx$, here, the estimated value of b demonstrates the association between the dichotomous response variable (log odds), D, and predictor X. Specifically, positive b replicates increasing risk of D as exposure increases and negative b indicates decreasing risk as the level of exposure increases.

The multiple logistic regression model consists of 2 or more predictors over the log odds and is demonstrated as, $Log\left(\frac{P_{x_1 \ldots\ldots x_k}}{1-P_{x_1 \ldots\ldots x_k}}\right) = Log(oddsforD|X_1 = x_1 \ldots., X_k = x_k) = a + b_1x_1 + \ldots.. + b_kx_k$

Here, a refers log odds of D at the baseline level means zero scales of all the risk variables. Moreover, the interpretation of the model is based on the log odds ratios in the form of value of bs obtained from the one unit risk increase in the predictors x_1, ……… x_k after the model run, for instance, b_1 is the log Odds Ratio associated with a unit increase in the scale of X_1, assuming all other risk variables in the model constant and no interaction existed. Many studies (Bulte et al., 2005; Hotton, 2011; Imai et al., 2015; Young et al., 2017) have used logistic regression to establish the environment-disease relationship in precise way.

2.4.3. Likelihood functions

If p is the proportion of the observed data, likelihood function is the plot of unknown proportion p, and can be expressed as, $L = P\ (data|p)$, where, P (data$|p$) is probability of maximum chance to choose among values of *p*. The maximum of likelihood function and log-likelihood function lie at the same point, however the use of log likelihood function is maximum for the reason of more precision of estimators. If the logistic regression models treated with maximum likelihood estimation, considering population based data, a complete likelihood function (L^*) is the product of individual likelihood contribution, as given by, $L^* = \prod_{i=1}^{n} P(D_i|X = x_i) = \frac{e^{-(a+150b)}}{1+e^{-(a+150b)}} \times \frac{e^{-(a+160b)}}{1+e^{-(a+160b)}} \times \ldots\ldots$

Besides the logistic regression estimates, the likelihood function is useful to obtain confidence intervals and hypothesis testing methods by Wald method (to calculate a confidence interval of b), score method and likelihood ratio method. This functional relationship is used by a study aimed to identify the relationship between the air pollution and respiratory diseases (Souza et al., 2018).

Beyond the linear relationship, if researcher intends to go beyond the logistic regression to further investigate whether there is some curvature in the relationship, a quadratic model given as log $[p/1\text{-}p]=a+(b+c(x))(x)$ can be used to obtain log odds ratio, where positive value of *c* indicates the log odds of *D* increases as *x* increases, and negative value of c explains log odds of *D* increases as *x* decreases. None of the study is found reaching for this level of investigation.

2.4.4. Cox regression model

For a setting of small cumulative risk, OR and constant RH are same but for a complex and multiple risk exposures, that is, different level of risk exposures for population subgroups; the relative hazard in terms of hazard function with slope c can be expressed as; $\log[h(t|X = x)] = \log h_0(t) + cx$, which is called Cox regression model or Proportional hazard model. In the model, $h(t|X=x)$ is the hazard function at time *t* for the subpopulation whose exposure level is $X=x$, function $h_0(t)$ is known as the *baseline hazard* function at exposure $X = 0$. The coefficient *c* is formally interpreted as the log Relative Hazard associated with a unit increase in the level of *X*. Alexeef et al. (2018) used cox proportional model to gauge the relationship between the cardiovascular diseases due to traffic related air pollution. McGregor et al. (2019) conducted survival analysis to assess the mortality hazards associated with the daily behavioral activities, using this model. Moreover, cox proportional hazard regression model is also used by Moolgavkar et al. (2017) to observe the changes in risk factors and smoking habit being based on the relative risk estimates. The same model used by Horton et al. (2019) to determine the association between blood lead level and subsequent Alzheimer's disease mortality, taking into consideration with impacts of competing risks, design effect and adjusted hazard rate ratio.

3. Economic evaluation methods for environmental health

Economic valuation is anthropocentric that always seeks the efficiency, optimality and sustainability predominantly in terms of monetary or numerical measures. Efficiency, most often appears as the necessary condition of optimality, leading to sustainability as the moral obligations. Basically, environmental effects possess non-use value that reflects in terms of human health change, better to be evaluated through household based datasets. Here, the economics of environmental health mainly seeks the specific methodology in the evaluation of effects on human health attributed to environmental change experienced by the community.

3.1. Burden of diseases (DALY and QALY)

The estimate of years of life lost (YLL) due to premature death and the estimate of years lived with disability (YLD) using DISMOD II method (Yoon et al., 2014) combinely releases the disability life adjusted years (DALYs). A study (Prüss-Ustü;n et al., 2016) based on the disease burden in terms of DALYs explored that cardiovascular diseases, diarrheal diseases and lower respiratory infections are attributed to ambient and household air pollution, and water, sanitation and hygiene. The same paper using comparative risk assessment methods explored that 56% of DALYs are attributable to the environment in the present global scenario.

DALY is the most popular measure since the decade of 1990s to demonstrate the economic losses of human disease burden induced by environmental changes (McMichael et al., 1997). This measure of evaluating the disease burden seems in priority of WHO, since it has used DALY for evaluating burden of diarrhea attributable to inadequate water, sanitation and hygiene in South East Asia (WHO, 2017). Another study considering DALY as the measure of malnutrition, diarrhea and malaria burden in global context inferred the use of DALY yields better results than mortality of population (Ebi, 2008). Some other national and international studies (Ebi, 2008; Ostensson, 2001; Young et al., 2017; Robertson et al., 2018; Rojas-Rueda et al., 2019; Hofstra et al., 2019) have potentially demonstrated the environment induced human disease burden in terms of DALY. Another recent study (Tong et al., 2019) developed probabilistic risk assessment model to explore contamination levels and health effects of automobile foundry dust, in terms of DALY. Recently, WHO has developed some health economic tools such as HEAT, isThat etc. for the assessment of disease burde in terms of DALY and other economic loss from health exacerbation induced by environmental change.

Quality-adjusted life years (QALY) is another popular measure for deasease burden used by a study (Stephen and Barnett, 2017) to evaluate the health vulnerability from the climate change. Another study by Kansal et al. (2019) used QALY as a measure of incremental cost effectiveness ratio in the assessment of empagliflozin treatment in people with diabetes and cardiovascular diseases. However, a study stated that QALY is less useful to be consistent with the changes in the individual utility changes and is never consistent with the changes in mortality and morbidity, and omits the non-health related effects of environmental policy (Freeman, 2006). Similarly, use of QALY in health economic evaluation is found unrealistic compared to other alternative assessment methods as suggested by Johnson et al. (2019).

3.2. Cost of illness

A global assessment of disease burden from environmental risks conducted by WHO explored that the cost of illness approach on total prevalence of disease is poorly used and in practice (Prüss-Ustü;n et al., 2016). Few south Asian countries has the current cost of illness evidence to be used in economic evaluation (Pant, 2013; Paudel, 2018; WHO, 2009), because of which, WHO also seems aware to develop the cost of illness due to the overall disease prevalence of each member country in the scenario of global environmental change. Evaluating cost of illness might be quite complex in the context and coverage of developing countries because of the data availability and inclusive data collection techniques in practice. However, two studies of Nepal successfully explored the cost of illness in the context of Nepal, one with the asthma caused by indoor air pollution (Pant, 2013) and another overall disease prevalence associated with change in temperature (Paudel, 2018), however cost of illness from the combined effects of environment is still unreached area of researcher.

3.3. Cost benefit analysis

Cost benefit analysis (CBA) is a tool to evaluate the interventional programs, either during the implementation or prior to the implementation of the program, whether the program is worthy to invest or not. Economic CBA covers advanced extra issues rather than financial CBA, for example, economic CBA covers the evaluation of non-tradable goods as well. Environmental and health issues are mostly the non-tradable goods, therefore CBA could be the best option for the evaluation of any interventional program related to environmental health.

A comprehensive study (Adhikari and Supakankunti, 2010) concentrating the consequences of neglected tropical diseases in terms of economic evaluation showed the usefulness of CBA and its potential as motivating factor for the subjects of interests. Similarly, an international study seemed preferred to use CBA to obtain the economics of health and climate change (Hotton, 2011). Moreover, some studies (Aslam et al., 2017; Klose, 1999) in the comparison of cost and consequences of the programs implemented over the non-tradable goods have undoubtedly employed CBA for the sake of reaching decisive decision. However, CBA cannot yield the comparison for the cost effective best options as cost effectiveness analysis can.

3.4. Cost effectiveness analysis

Cost effectiveness analysis (CEA) suggests the general decision in the selection among program completion methodological options for the same level of health outcomes from the investment that ensures the minimum cost for a given change in benefits. Specifically, Gren and Isacs (2009) suggested that CEA is the best option for assessing replacement value of wetlands in a cost effective allocation of measures for given nutrient abatement targets, if wetlands are renovating into arable lands. From the review of literatures since 1990, most of the environmental health related papers wrapped with recommendation about the strong use of CEA (Hotton, 2011), however, WHO and other some international studies (Arrow et al., 1996; WHO, 2013; WHO, 2014) have strongly employed and gave some guidelines for the apposite use of CEA.

Cost utility analysis falls under a type of CEA. Pereira et al. (2019) performed cost-utility analysis of Colerectal cancer from a societal perspective in Portugal comparing two strategies: blood genetic testing by the age of 40 versus no genetic screening under different assumptions of the cost of genetic testing and expected risk. Similarly some international studies (Diep et al., 2018; Chen et al., 2018; Börger et al., 2018) have used cost utility concept for health system measurement, devoting only on health system indicators only.

Cost estimates obtained for CBA can be used for CEA, but, not like the CBA, the health outcomes as the benefits can be used in physical terms in CEA. It is simple to understand that benefit components of health programs are commonly more sensitive compared to components of costs (Adhikari and Supankunti, 2010). So the better option might be first to find the less sensitive physical benefits through CEA of the health program as an initial fixed level of outcomes (output variable), then if those physical benefits can be monetized, one can go further for a CBA.

3.5. Willingness to pay

Willingness to pay (WTP), one of the preferred contingent valuation method, is a stated or revealed preference tool for benefit estimation from the change in consumer's utility of non-tradable goods and services. In research methods, positive willingness to pay informs the higher marginal benefit from the intervention programs than marginal cost incurring by consumer in the existing scenario. Though WTP is supposed to be debatable issue in terms of its validity, a prudent use of WTP for yielding benefit of non-tradable goods provides a single precise and accurate elicitation of changed utility value. With the review of papers since 1990 to till the data, mostly the environmental issues and few health economics papers seems employed the WTP method for benefit and utility elicitation.

Sinden et al. (2008) in their methodological discussion prioritized WTP as the major tool in the valuation of the gains from the protection of biodiversity. Similarly, Choe et al. (1996) used WTP method for evaluating the economic benefits of surface water quality improvements in developing countries. Moreover, Arrow et al. (1996) explained the use of WTP to elicit benefit while employing economic CBA in scrutinizing the program. Ostenssion (2001) have argued that WTP is central to the assessment of environmental damage. Besides, some potential studies (Alberini et al., 1997; Bulte et al., 2005; Umeh and Feeley, 2017) also have used WTP for the evaluation of environmental health issues with strong modification in methods and with adequate validity.

3.6. Travel cost method and hedonic pricing method

Travel cost method infers use value or recreational valuations from observed behavior, including travel costs to value site attributes. Similarly, hedonic pricing method is also an indirect method of evaluating monetary measures of environmental goods, specifically for air pollution. Both the methods were popular before a decade. Recently, these methods are not found in wide use for environment related health issues. Though, travel cost method is used by some classical studies (Bishop and Heberlein, 1979; Navrud and Mungatana, 1994; Nunes and Bergh, 2004), hedonic pricing method is prioritized by very few papers (Mendelsohn and Olmstead, 2009; Ostensson, 2001) to evaluate environmental amenities relating to health effects.

3.7. Human capital approach

Human capital approach is mostly preferred for the health economic evaluation models. This approach assumes the productivity gains from a healthy person after the recovery of ill person, taking reference of life expectancy. Lenk et al. (2018) used this approach to evaluate socioeconomic benefit of neglected tropical disease control. Arrow et al. (1996) also argued about the use of human capital approach as an alternative for benefit estimation of environmental improvement and human health protection. Similarly, Yongguan et al. (2001) employed this approach for the evaluation of environmental cost of water pollution in china.

3.8. Data envelopment analysis – efficiency and productivity assessment

Efficiency stands for doing things right for the maximum outputs to input ratio. Frogner et al. (2015) used efficiency modeling technique to evaluate the efficiency of health system taking consideration of environmental variables. Data Envelopment Analytical tool is generally used to identify the efficiency and productivity of health system. Similarly, efficiency modeling is major tool to ensure the sustainability of healthcare management system in terms of health outcomes (Joumard et al., 2008). Silwal and Ashton (2017) also investigated the efficiency and productivity of Nepalese hospitals using this tool.

Based on the above review of methodological procedures in the existing literatures separating into epidemiological and economic impacts, it is clear that the existing literatures are lacking with the complete methodological procedure for evaluating the aggregate environmental effects on human health. Therefore, this study henceforth presents a model methodology for the economic evaluation of environmental health issues, beyond the epidemiological studies, by creating a set of research questions and methodology for answering the questions that is directly related to environmental health through the perspective of microeconomics.

4. A model methodology for economic analysis of environmental health

A set of community based or demand side research question includes what are the major environmental determinants of disease prevalence and the relationship between environmental determinants and disease prevalence following the cost of illness, what is the health cost and adaptation cost incurred by household and what is the household benefit from the improvement of environment at community level. Based on these research objectives, a model methodology is adequately explained with some recent publications and econometric theories.

After setting research design and study variables; first objective, the determinants of disease prevalence at household level, can be assessed by the use of Probit model as explained by Paudel and Pant (2018) using cross-sectional analytical design with theoretical base. Similarly, the second objective is also addressed by another recent study (Paudel, 2018), identifying the disease-environment relationship using time series analytical evaluation design. For third and fourth objectives, environmental health assessment in terms of health care economic cost integrates a set of complex methodological approaches including both epidemiological and economic impact analysis for the development of coefficients of environmental change. Environmental imbalance increases the disutility of unhealthy consumers because of increasing health recovery compensation cost. Cost and benefit estimation methods are explained hereafter.

4.1. Estimation of household cost

Cost is the input for the recovery of damage made by environmental or other changes. Generally, households cost might be an accumulation of out of pocket spending on curative and preventive health inaction cost, adaptation cost and natural hazard cost where prevalence of diseases is rampant due to extreme environmental degradation. This section may cover the entire household cost estimation method for the fulfillment of third objective of the hypothesized research.

4.1.1. Health inaction cost estimation

Cost is the input to fulfill the expectation of better health output. The costs incurred by the household for the treatment of diseases and adaptation activities can be calculated using the ingredients approach through reviews of published and unpublished literature, direct interviews, and focus group discussion.

1) Direct Cost: Direct cost of health care includes both curative and preventive costs incurred by the household from out of pocket payment. The direct cost of household can be calculated from ingredient approach. Direct curative cost (a_1) includes transportation cost, medicine cost, food and water, equipment rent and registration fees. Direct preventive cost (a_2) includes the out of pocket payment of household made for the preventing activities such as payment for mosquito nets, nets for windows and doors, toilet cleaning devices, water treatment devices, skin care products and insecticide/pesticides for the protection of family from disease occurrence at home.
2) Indirect cost: It includes time cost for cure of the disease and prevention from the diseases. Curative time cost (b_1) of patient and caregiver includes bed rest days, hospitalized days and time to reach to hospital for the recovery of illness. Similarly, preventive time cost (b_2) aggravates the time spent for the fitting net on bed, time for solid waste management etc. Both the curative and preventive indirect costs can be estimated from the conversion of time loss in to monetary term from a relation of government wage rate (For example, NPR 517) per day of working 8 h.

4.1.2. Adaptation cost

Indirectly, every adaptation cost of household is linked to health preventive cost and others, but here, the adaptation cost of household (c_1) can be considered without any overlapping with health preventive cost. Reconstruction of house, change in house infrastructure, payment for fan, refrigerator, air-conditioner, seasonal especial clothes, reservation tank for a long drought, water outlet for heavy rain and lightning prevention measures are the major ex-post cost of household for the adaptation of extreme environmental degradation or hazards. These costs can be estimated from the cost data obtained by direct interview in the study area.

4.1.3. Natural hazard cost

Some climatic components such as draught, heavy rain, flood, thunderstorm and heat waves could be intermittent in any specific territory. These natural disasters are directly associated with loss of property of households. With this reality, the natural hazard cost (d_1) can be estimated from the loss incurred by the households due to different natural hazards through data obtained by direct interview response in each sample household in the study area.

Therefore, total household cost = health inaction cost + adaptation cost + cost of natural hazards

Mathematically,

Household cost induced by environmental degradation = $\mathbf{a_1} + \mathbf{a_2} + \mathbf{b_1} + \mathbf{b_2} + \mathbf{c_1} + \mathbf{d_1}$

Importantly, further the effect of health cost on household economy can be identified from finding the average percentage of total income spent by households on health. Besides, the cost of illness can be alternative to identify the economics of disease-environment relationship, extending with sensitivity analysis.

4.2. Relationship between health inaction cost and adaptation cost

Environmental degradation can be the cause of adaptation cost that might be affected by household health care cost. For the sake of finding relationship between these two costs, a utility approach can be linked with this particular study. Let U_1 be the utility of an individual from a health status (H) and income y with other non-health factors (NH), subject to health care cost (C).

$$U_1 = f(H, y, NH) s.t.C \tag{1}$$

Similarly, U_2 be the utility of an individual from the adaptation mechanism (A) and other than adaptation activities (OA) for the environmental hazards, subject to adaptation cost (AC)

$$U_2 = f(A, y, OA) s.t.AC \tag{2}$$

Then, total utility (U) from the health recovery and adaptation is subject to total cost (C). As such, U takes the form of from the combination of (1) and (2),

$$U = f(H, y, A) s.tC \tag{3}$$

For the identification of relationship between H and A, a functional form of them can be as,

$$\mathrm{A} = \mathrm{f}\ (H,\ y,\ X) \tag{4}$$

where, X is control variables.

Alternatively.

Following the two approaches of Grossman (1972) and Cropper (1981), let us consider an individual whose decision on adaptation for environmental problems attributing to health cost is to choose time paths for his health capital as well as for non-health consumable goods in an optimal way. The decision problem of individual can be expressed by an inter-temporal utility function U,

$$U = \sum_{t=0}^{n} m_t u_t, \quad \text{where} \quad U_t = u(h_t, z_t, Y_t) \tag{5}$$

where, m_t = weights determined by individual's rate of preferences.

u_t = utility in period t
h_t = services of health capital
z_t = non-health commodity consumed by the individuals

Modifying the related function given by Killingworth (1983) in the optimization problem, health capital stock as measured in units of healthy time can be assumed,

$$h_t = h(H_t), \frac{\partial h}{\partial H_t} > 0 \tag{6}$$

and non-health consumable commodities as,

$$z_t = z(X_t.Y_t), \tag{7}$$

where, X_t denotes human capital (e.g. education), Y_t as income.

The marginal change in the stock of the health capital over time with investment I_t (as a proxy of adaptation (A_t)) with depreciation of the existing stock is written as,

$$\Delta H_{t+1} = H_{t+1} - H_t = I_t - \delta H_{t+1} H_t \tag{8}$$

where, δ is rate of depreciation in health capital.

At the same time, the individual tries recover his health capital by investing on adaptation (A_t), on medical care M_t , income Y_t and time inputs TH_t and other exogenous parameter (X_t),

$$I_t = I(A_t, M_t, .Y_t, TH_t, X_t) \tag{9}$$

Therefore the individual's inter-temporal optimization problem deals with the problem of discrete optimal control (Leonard and van Long, 1992). Now, the objective is to maximize U.

$U = \sum_{t=0}^{n} m_t u[h(H_t, Z_t, Y_t)]$ subject to equation (7)–(9); considering other additional restrictions on work, income and expenditure on M_t and X_t.

Moreover, the equation (8) can be rewritten as suggested by Ried (1994) as,

$$\Delta H_{t+1} = \left(\frac{\partial A_t^I}{\partial P_t^M}\right)^{-1} M_t - \delta_t H_t, \tag{10}$$

where, $A_t^I(A_t)^z$: Marginal cost of gross investment for adaptation.

And $P_t^M(P_t)$: Price of medical care for period t.

In our case, the optimality condition for the stock of health capital now can be written as,

$$W_t \frac{\partial h}{\partial H_t} = A_{t-1}^t(1+r) - A_t^I(1-\delta_t), \tag{11}$$

where, W_t is wage rate, r is rate of interest.

Then, in order to get estimable equation for the adaptation at household level due to higher medical expenditure, the logarithmic function can be written as,

$$LnA_t = \frac{\partial A_t^I}{\partial P_t^M} + Ln\delta_t H_t + \Delta H_{t+1}\Big) \tag{12}$$

and the logistic regression model can be expressed with assumption a binary random variable A_t (constant variance and non-zero mean) with value 1 for the probability P_h and 0 with probability (1-P_h).

$$P_h = P(A|_{H=h}) = \frac{1}{1+e^{(-a+bh)}} \tag{13}$$

Alternatively, if it is assumed that log odds of adaptation cost linearly changes with change in h, then the probability of changes in cost can be shown in logistic regression equation as,

$$Log\left(\frac{P_h}{1-P_h}\right) = Log\left(oddsforP\left(A|_{H=h}\right)\right) = a + bh \tag{14}$$

where, a and b are parameters, and$P(D|_{H=h})$ = P_h = Risk for high or low health cost.

Therefore, to identify the determinants of the adaptation cost at i household within t time period, the final logistic regression equation for this study then takes the form,

$$A_{it} = \beta_0 + \beta_j H_{ijt} + \beta_k X_{ikt} + \beta_l Y_{ilt} + e_{it} \tag{15}$$

Further, the specific form for the Probit regression equation for the relationship between adaptation cost and health care cost along with other control variables can be set as per the need. The relationship of health cost and adaptation being positive or negative could equally demand the analytical concept of improvement over the loss of environmental quality. Since health cost is revealed cost while environmental goods as non-tradable goods should be treated with stated preference theory. The relationship between H and A at constant income Y demonstrates that E_1E_2 is the recovery cost to avoid the environmental hazards from the inward shift in iso-quant curve from q_1 to q_2 (Fig. 2).

The loss in utility to be recovered from equivalent surplus from the change in environmental hazard is the willingness to pay of the individual household. Therefore, adaptation cost is more concerned with environmental deterioration. At the same time, an individual can attain an equilibrium level of utility from generating E_1E_2 level of equivalent surplus from environmental improvement. If the relationship is positive, health cost is apparent with positive impact on adaptation cost at household level. Conversely, for negative relationship or almost no relationship, adaptation cost of household is motivated by other than health cost increment. This completes the methodology for third objective of the hypothesized research objective.

4.3. Estimating benefit with willingness to pay method and its determinants

Contingent valuation methods are typically used to measure the value of non-market goods in environmental economics but they have also been used in health economics and health services research to measure WTP for health services (Klose, 1999; Ostensson, 2001). In the investigation of Kenneth Arrow and Robert Solow to investigate this method over the hedonic pricing and travel cost method for the valuation of environmental goods, this method was preferred to cover all possible benefits or the anthropocentric instrumental value of environmental goods only if studies were conducted to a rigorous set of guide-lines which were explicitly spelt out (Ostensson, 2001).

Owing to the environmental goods as non-marketed, the benefit estimation of these goods is quite indirect but from directly affected agents within the degrading environment. Among several methods of eliciting household benefit from the improvement of environmental situation, the best method is still supposed to be willingness to pay of household for the avoidance of possible natural hazards and possible health inaction cost. By the nature of this hypothesized research linking the environmental consequences over the human health, contingent valuation method or willingness to pay method can be common to use in the valuation of non-marketed goods if sufficiently valid to use within the hypothetical market.

In this particular case, research concerning WTP directly matches with a concept validated by Hanemann, (1984) on double bounded dichotomous choice method having the advantage of placing a low burden on the respondents compared to open-ended questions, because respondent could be set free to response for any level of initial bid with a frequent reminding their level of income/wealth and family suggestions. For this, first, the respondent should be asked whether s/he would be willing to pay on an initial bid. Then a second bid, lower or higher than the first one depending on the initial response, is assigned. Therefore, there might be three cases depending on the response: WTP lies somewhere between the two bids ('yes'-'no', 'no' 'yes') or below the second bid ('no'-'no') or above it ('yes'-'yes'). Based on this approach, model is formulated below.

For example, let A_i be the first bid, $A^{H}{}_i$ $(A_i < A^{H}{}_i)$ be the higher second bid when the individual responds "yes" to the first bid, and $A^{L}{}_i$ $(A_i > A^{L}{}_i)$ be the lower second bid when the individual responds "no" to the first bid. When each respondent is presented with two bids, there are four outcomes: (a) both answers are "yes" (yes-yes); (b) both answers are "no" (no-no); (c) a "yes" followed by a "no" (yes-no); and (d) a "no" followed by a "yes" (no-yes) whose binary-valued indicator variables are $X^{YY}i$, $X^{YN}i$, $X^{NY}i$, and $X^{NN}i$, respectively such that:

$I^{YY}i = \mathbf{1}$ (*i*th respondent's response is "yes-yes")
$I^{YN}i = \mathbf{1}$ (*i*th respondent's response is "yes-no")
$I^{NY}i = \mathbf{1}$ (*i*th respondent's response is "no-yes")

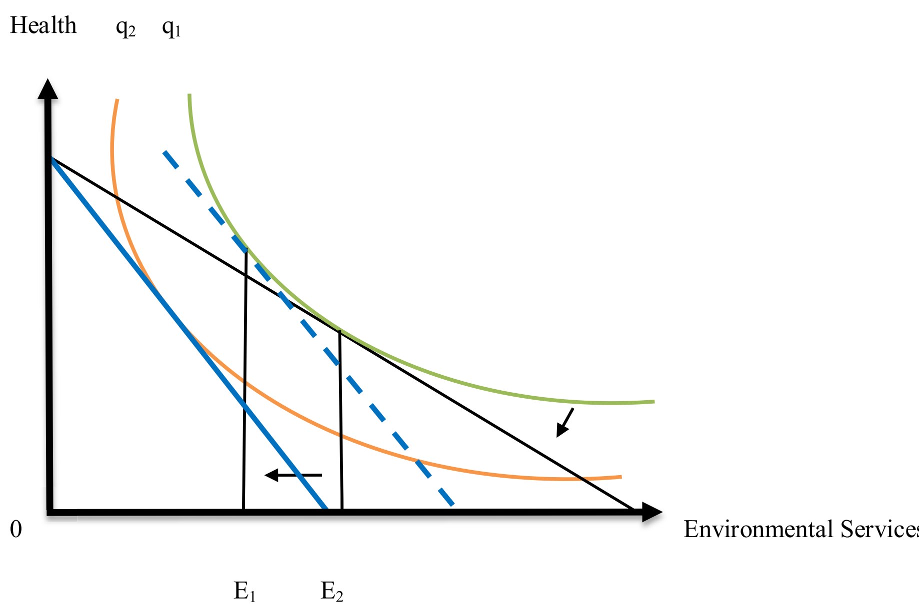

Fig. 2. Household welfare loss from natural hazard.

$I^{NN}i = \mathbf{1}$ (*i*th respondent's response is "no-no"). Accordingly, log likelihood function can be derived. Based on this theory, the following method for eliciting the household WTP is hypothetically formulated.

4.3.1. Method of eliciting household willingness to pay

Societal benefit (equivalent surplus) is supposed to obtain with willingness to pay method. A hypothetical situation should be created explaining a scenario given below and asked a question for their response (benefit) setting them free for any level of response or not. For the sake of validity issue in WTP method; setting the respondent free to response with the combined voice of family, focus group discussion among locally popular people and local expert's suggestions management can be carried out to make the estimation free from the starting point bias and range bias, but criterion validity should be made for avoiding the biases in this methodological issue. A model of hypothetical background and question is given below:

… ……the incidence and intensity of different diseases along with climate and environmental disaster that you have been facing … … a hypothetical situation where you are safe from all these climate caused diseases. … the better situation of some environmental components such as safe water management, air quality assurance; so that your locality will have least chance of diseases incidence and prevalence … reduction of disease incidence, improve the individual/household/community behavior through above mentioned intervention. Therefore, you are required to pay one time out of pocket payment within this year.

Question: How much are you willing to pay in the intervention at once if your money completely protect from any diseases mainly caused by environmental degradation and natural disaster afflicting your locality? NPR… ….

4.3.2. Econometric treatment for determinants of willingness to pay

Public benefit or welfare calculations, based on the compensating and equivalent variation, consider at the heart of economic policy analysis. However, the change in environmental services are mainly concerned with compensation surplus (CS) and equivalent surplus (ES) for the reason that quality/quantity change in the consumption level for the environmental service is beyond the individual's control. If it is considered a deterioration in the environment (E), and examine CS and ES for that case, then CS is willingness to accept compensation for the lower E while ES is willingness to pay to avoid it. Now, WTP of individuals can be captured for the improvement of the environmental services, based on the hypothetical statement, with new utility level of the community people, so the concern can be linked with equivalent surplus (ES). A thorough derivation of equivalent surplus can be modeled with the following formulation.

4.3.3. Model formulation

Let us consider that an individual attains utility u from the use of money income (Y) under a degrading environment scenario for the improvement of environmental quality from q_0 to q_1, where $q_1 > q_0$; an individual who has felt a need of environmental improvement or to avoid the hazards cost is willing to pay (h = 1) or unwilling to pay (h = 0). If he wants to pay, the individual utility is $u_1 = u(1, q^1, y; s)$and if he does not, his utility is$u_0 = u(0,\ q^0,\ y; s)$, where s is the vector of explanatory observable variables. Therefore, utility function $u(h, q, y; s)$now helps to generate the stochastic structure of the statistical binary response model.

If u_0& u_1 are random variable with mean $v(0, y; s)$ and$v(1, y; s)$, the utility equation takes the form,

$$u(j, q_j, y; s) = v(j, q_j y; s) + \varepsilon_j, j = 1, 0 \tag{16}$$

where $\varepsilon_0$and ε_1 are random variables with zero mean.

From this sense, the individual will accept the offer of environmental improvement if

$$v(0, y - A; s) + \varepsilon_0 \geq v(1, y; s) + \varepsilon_j, J = 1, 0 \tag{17}$$

and reject if otherwise. Where, A is adaptation mechanisms (cost).

Now, a rational consumer of environmental services tries to maximize his utility by responding a random variable with probability distribution given by.

$$P_0 = \Pr(YesWTP)$$

$$P_0 = \Pr\{v(1, q^1 y - A; s) + \varepsilon_1 \geq v(0, q^0 y; s) + \varepsilon_0\}$$

$$P_1 = \Pr(NoWTP) = 1 - P_0 \tag{18}$$

Consider, $\eta = \varepsilon_1 - \varepsilon_0 \& F_\eta(.)$is a conditional function of η.Then the WTP probability function becomes,

$$P_0 = F_\eta(\Delta v) \tag{19}$$

where, $\Delta v = v(1, q^1, y - A; s) - v(0, q^0, y; s)$and $\Delta v$is change in mean random utility or individual equivalent surplus from the environmental improvement.

Further, probability function in equation (18) can be written in Logit model that takes the form,

$$P_0 = F_\eta(\Delta v) = (1 + e^{-\Delta v})^{-1} \tag{20}$$

Again, the utility difference Δv can be a beauty to explain binary response model as the outcome of a utility maximizing choice. It releases the criteria for utility maximization model in binary response.

If we suppose,

$$v(j, q, y; s) = \alpha_j + \beta y, \beta > 0, \tag{21}$$

with suppressing s , then Δvbecomes,

$$\Delta v = (\alpha_0 - \alpha_1) + \beta A \tag{22}$$

& discrete choice model becomes,

$$P_0 = F_\eta(\alpha + \beta A) \tag{23}$$

similarly, in semi log form,

$$v(j, q, y; s) = \alpha_j + \beta \ln y, \beta > 0, j = 0, 1 \tag{24}$$

And finally,

$$\Delta v = (\alpha_0 - \alpha_1) + \beta \ln(y - A) - \beta \ln y \tag{25}$$

which is equivalent to

$$\Delta v = (\alpha_0 - \alpha_1) + \beta \frac{A}{y} \tag{26}$$

To measure the welfare fitting binary response model if an individual is losing his utility by environment quantity$E$that satisfies

$$P_1 = \Pr(E > A) = 1 - G_E(A) \tag{27}$$

where, E the individuals' maximum willingness to pay that satisfies,

$$u(0, q^0, y; s) = v(1, q^1, y - E; s) \;\; Or \;\; E = y - m[v(1, y; s) - \eta, 1; s] \tag{28}$$

and $G_E(.)$is conditional function of$E$ with welfare measurement, in terms of means.

$$E* = \int_0^\infty [1 - G_E(A)] dA \tag{29}$$

This is the total value of the consumer's surplus from the improvement in environmental services. To identify the actual equivalent surplus of the consumer, let us consider another measure of an environmental quantity E^{**}, that satisfies,

$$E\{u(0, q^0, y; s)\} = E\{u(1, q^1, y - E**; s\}] \tag{30}$$

Again, a third measure is considered E^+ which is the medium of the distribution$G_E(.)$, then E^+ can be written as,

$$\Pr\{(u(1, q^1, y - E^+; s) \geq u(0, q^0, y; s)\} \tag{31}$$

Now, the quantities E^+ and E^* can be expressed as,

$$E* = y - ye^{(\alpha_0 - \alpha_1)/\beta} E\left\{e^{\eta/\beta}\right\} \tag{32}$$

$$E^+ = y - ye^{(\alpha_0 - \alpha_1)/\beta} \tag{33}$$

This calculation model helps to identity the total equivalent surplus from environmental improvement satisfying $q_1 > q_0$ which allow formulating actual welfare,

$$E* = ES = \int_0^\infty [1 + E^{-\delta_0 - \delta_1} \ln A]^{-1} dA = -e^{-\delta_0/\delta_1} \frac{\Pi/\delta_1}{Sin\left(-\Pi/\delta_1\right)}, 0 > \frac{1}{\delta} > -1 \tag{34}$$

Above equations (26) and (34) strongly open to generalize and evaluate public welfare from of non-tradable environmental goods by the use of the logit model for the binary response of an individual, with several effects. Then, the linear form of the equation (26) takes as,

$$y_{ij} = \beta_0 + \beta_i x_{ij} + \varepsilon_{ij}, \tag{35}$$

where, y_{ij} is household's willingness to pay with j = 1 (willing to pay), 0 (not willing to pay); or 1 = Yes, and 0 = No response of ith household. x_{ij} a vector of explanatory variables including individual, environmental, demographic and household characteristics, and ε_{ij}, a random component following a normal distribution with mean zero and constant standard deviation.

Therefore, the general form of the binary logistic regression equations is.

Model 1: $y_{ij} = \beta_0 + \beta_i x_{ij} + \varepsilon_{ij}$, where, x_{ij} is the vector of socioeconomic variables.

Model 2: $y_{ij} = \beta_0 + \beta_i x_{ij} + \varepsilon_{ij}$, where, x_{ij} is the vector of socioeconomic variables and environmental variables.

Model 3: $y_{ij} = \beta_0 + \beta_i x_{ij} + \varepsilon_{ij}$ where, x_{ij} is the vector of socioeconomic, environmental and household behavioral variables.

This completes the fourth objective assumed. Hence, the model methodology for the economic analysis of environmental health issues can take the environmental health researcher to the fulfillment of theoretically expected set of objectives from microeconomic (demand) perspective or household side.

5. Conclusion

This paper has overarched the major methodological issues available in literatures since 1990 to 2019. Based on the review of the potential papers, odds ratios are found the most popular and easy to explain for the dichotomous response variable, following the probit regression model. But, cox regression model is rarely used while regression with interaction and confounding is poorly addressed. On the other hand, many papers have been popularly using DALY and QALY as measures of disease burden but limited evidence are available using these measures while performing particularly the economic evaluation of environmental health issues. At the same time, CBA and CEA are recommended to use for the environmental protection programs. WTP is commonly used in recent research in the estimation of non-use benefit of environmental programs. Based on the paucity of strong methodology in the literature, all available model methodologies for the sake of environmental health research are reviewed. Economic perspective is successfully presented in the paper which might have potential power to encourage the researchers seeking the alternative methods for the economic evaluation of environmental health issues, including non-use value of health benefits.

Declaration of competing interest

None.

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Abbreviations

CBA	Cost Benefit Analysis
CEA	Cost Effectiveness Analysis
DALY	Disability Adjusted Life Years
QALY	Quality Adjusted Life Years
OR	Odd Ratios
RR	Relative Ratios
WTP	Willingness to Pay
WTA	Willingness to Accept
WHO	World Health Organization

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Author's contributions

Uttam Paudel prepared the manuscript. Shiva Raj Adhikari and Krishna Prasad Pant added inputs in it, and all the authors finalized and approved the manuscript.

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