EEPSEA
2016-RR9

Estimating the Benefits of an Improved Storm Early Warning Service in Vietnam: An Application of Choice Modelling

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WorldFish

Published by WorldFish (ICLARM) – Economy and Environment Program for Southeast Asia (EEPSEA)
EEPSEA Philippines Office, WorldFish Philippines Country Office, SEARCA bldg., College, Los Baños, Laguna 4031 Philippines; Tel: +63 49 536 2290 loc. 196; Fax: +63 49 501 7493; Email: admin@eepsea.net

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ISBN: 978-971-9994-68-8

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Suggested Citation: Nguyen C.T. 2016. Estimating the Benefits of an Improved Storm Early Warning Service in Vietnam: An Application of Choice Modelling. EEPSEA Research Report No. 2016-RR9. Economy and Environment Program for Southeast Asia, Laguna, Philippines.

Estimating the Benefits of an Improved Storm Early Warning Service in Vietnam: An Application of Choice Modelling

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May, 2016

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ACKNOWLEDGMENTS

I would like to express my special thanks to Dr. Jackie Robinson, Prof. Wiktor Adamowicz, and Prof. Dale Whittington for their valuable instructions, comments, and suggestions, which improved this research immeasurably.

My sincere gratitude goes to Assoc. Prof. Nguyen The Chinh, Mr. Le Thanh Hai, Mr. Truong Tuyen, Dr. Le Ha Thanh, and the staff of Center for Hydro-meteorological Forecasting in Quang Nam and in Northeastern region. Without their assistance, it would not have been possible to conduct the surveys for this research.

I am grateful to Dr. Herminia A. Francisco and Ms. Catherine Ndiaye for their kind support toward this project. I gratefully acknowledge the financial support provided for this research by the Economy and Environment Program for Southeast Asia.

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EXECUTIVE SUMMARY

Vietnam is one of the most storm-prone countries in the Mekong region as it is situated close to the storm center of the Western Pacific. About 70% of Vietnam's population lives in storm-prone areas. Climate change could be responsible for the increased severity of storm risk in Vietnam. In recent years, intense storms have hit Vietnam more frequently, the storm pattern has been significantly different from the usual, and the fatalities caused by these storms have increased. Improving the storm early warning service could be one of the key measures to help Vietnamese people, especially the poor, to adapt to the more severe storm risks associated with climate change. To bring the adaptation measures into effect, external funding is an important additional resource to assist developing countries like Vietnam.

This research aimed to estimate the benefits of an improved storm early warning service. Given the limited resources available, the information on the benefits estimated by this research could be useful for the Government of Vietnam and to climate change donors in formulating optimal policies for climate change adaptation. Based on the literature review and on the several focus studies done in this study, Choice Modelling (CM) surveys with 1,014 respondents were designed and conducted.

The results showed that a Vietnamese household would be willing to pay 0.024% of their household income for the improvement of storm early warning service. The maximum benefit that can be derived from improving early warning service for storm in Vietnam was estimated to be about VND 3,322–3,771 billion (~USD 160–181 million). These results took into account the issues of hypothetical bias, which appeared to be consistent with the available results in literature. The results also suggested that the investments in early warning service for storm should be paid for the improvement of accuracy and the warning attribute of mobile phone short message.

1.0 INTRODUCTION

1.1 Research Problem

Vietnam is close to the storm center of the Western Pacific, which makes it one of the most storm-prone countries in the Mekong region. Each year, an average of seven storms make landfall on the coastal areas of Vietnam (CCFSC 2007; ISPONRE 2009). About 30% of the storms affecting Vietnam are classified as strong and very strong, with maximum wind speed of 89 kilometers per hour (kph) and >117 kph, respectively. The stormy season in Vietnam spans from June to December, with peak months in September and October (ISPONRE 2009). About 70% of Vietnam's population lives in storm-prone areas, with the majority of the most vulnerable located in Central Vietnam (IEDM 2008; Shaw 2006) (Figure 1).

According to the damage reports of Vietnam's Central Committee for Flood and Storm Control, the annual human casualties due to storms from 1989 to 2009 have been estimated at an average of 827 dead, injured, and missing people. The disaster risk indices provided by Mosquera-Machado and Dilley (2009) have cited Vietnam to be among the top 20 countries in terms of storm fatal risk. Imamura and Dang (1997) have indicated that the damages due to storms in Vietnam have been surprisingly high at more than 70% of the total damages from all kinds of natural disasters.

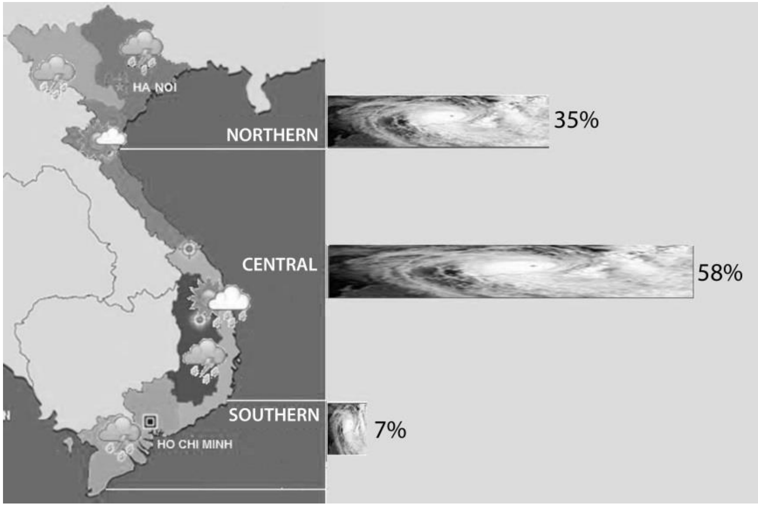

Figure 1. Frequency of storms affecting three mains regions of Vietnam from 1961–2009

Source: MONRE

Climate change is now being acknowledged to be present, with indications such as the increasing average global temperatures, which causes the increased severity of storm risk in Vietnam. In recent years, intense storms have hit Vietnam more frequently (MONRE 2009). Of the total strong storms that have affected Vietnam, the percentage of storms with intensity Level 13 and above has increased significantly from 7% to 36% (Figure 2). This increasing frequency of intense storms may be related to climate change. Elsner, Kossin, and Jagger (2008) have suggested that the increasing global temperature allows strong storms to become even stronger. Knutson et al. (2010) have also shown that global warming would cause the global average intensity of storms to increase by 2%–11% by 2100.

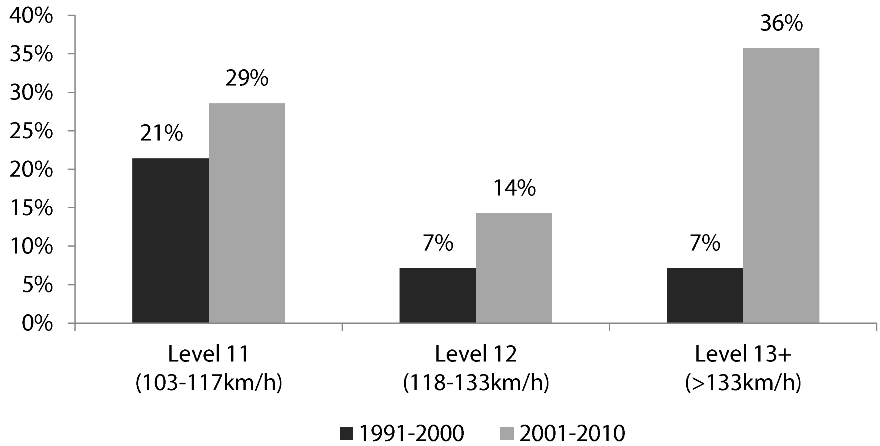

Figure 2. Increases in the frequency of intense storms in Vietnam

Source: MONRE

Climate change also appears to contribute to the changes in the pattern and direction of storms in Vietnam. Over the past few years, the storms that have hit Vietnam have been significantly different from the usual storm pattern (Shaw 2006). For example, storms do not usually pass through the Southern Vietnam; thus, it is considered to be the least-affected region in Vietnam by storms. However, the Southern Region has been hit with a number of storms in recent years (Figure 3). With such changes, the local people's usual disaster risk reduction practices may no longer be effective in responding to the hazards posed by storms. Without a timely and reliable early warning service, the more severe storm risk may cause larger and irreversible damages to the vulnerable Vietnamese communities living in the coastal areas. Figure 4 shows that the fatalities due to storms have increased in recent years.

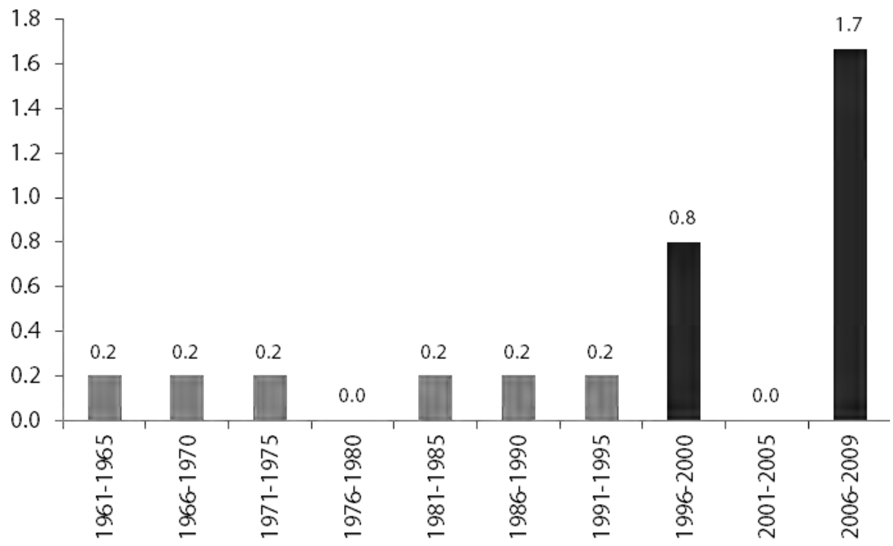

Figure 3. Increase in five-year mean number of storms affecting the southern Vietnam

Source: MONRE

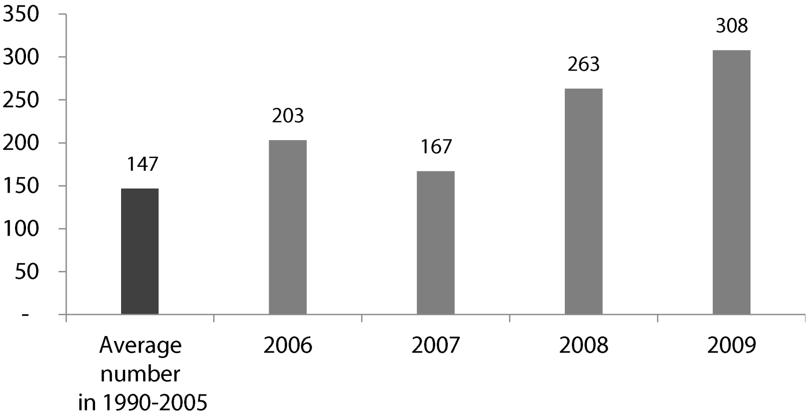

Figure 4. Fatalities caused by storms in Vietnam

Source: CCFSC

In Vietnam, the major source of meteorological services is the National Hydro-Meteorological Service (NHMS), which was officially established in 1976. When the Ministry of Natural Resources and Environment (MONRE) was established in 2003, NHMS became an operational unit under MONRE. In the organizational framework of NHMS, the National Centre for Hydro-meteorological Forecasting (NCHMF) is responsible for providing various hydro-meteorological and marine forecasts across the whole country in order to meet the growing requirements of socioeconomic activities and to prevent natural disasters.

The storm warnings issued by NCHMF are provided for free; it is the public's primary source of storm information, particularly in rural coastal areas. Storm information is provided such that people can assess the risk posed by the incoming storms, and they can decide accordingly how they should respond to the hazard. Storm warnings are often issued 24–48 hours before the expected landfall, which allows for adequate disaster risk reduction response time.

The components of a storm warning often typically consist of three components: (1) name of the storm, (2) current line tract and intensity, and (3) track and intensity forecast within the next 24–48 hours. NCHMF uses six types of storm warnings; urgent warnings are issued if a storm is about 300–500 kilometers (km) away from the area of landfall, if the storm is heading to Vietnam mainland within the next 24–48 hours, or if the "eye" of the storm is around 300 km from the mainland but is moving slowly.

There are several ways by which the public can access the storm warnings. Television and radio remain as the primary mode of communication for the storm forecasts (Huy 2009; Nhan et al. 2007). Local warning dissemination platforms such as sirens, fixed and portable loudspeakers, or door-to-door visits are also used to alert the public. The most effective early warning strategy for the most vulnerable households is the face-to-face mode of communication, which is delivered by officials and volunteers of the local Committee for Flood and Storm Control. For offshore communication, well-equipped fishing boats are warned of an impending storm through high-radio frequency or radio telephone. In addition, traditional methods such as signals using long bamboo poles or big fires, etc. are used to alert those who are in small fishing boats near shore (usually 2–15 km away from the main land) without any communication equipment. In case of nearby or emergency storms, the border police searches for these small boats to warn them personally.

However, the capacity of NCHMF may not be able to meet the demands of the more complex storm fluctuations that climate change causes. According to the report of NCHMF (2009), its monitoring network is composed of only a small number of stations, most of which are not automated. Moreover, NCHMF's monitoring network provides meteorological data that has low geographic and temporal coverage. Also, the numerical forecasting models of NCHMF are not systematically consistent with one another. In addition, NCHMF lacks experienced forecasters as a result of the inappropriate income policies.

Recognizing these issues hounding NCHMF, the Government of Vietnam plans to improve the agency's forecasting capacity. Under the Strategy for Development of Hydro-meteorological Service, which was ratified by the Prime Minister in 22 June, 2010 and will be operational until 2020, several important programs aimed at improving the capacity of NHMS have been implemented. From 2010 to 2015, four main programs have been implemented:

1. Modernization of forecasting technologies and monitoring systems for hydro-meteorological services (2010–2012);
2. Modernization of hydro-meteorological services (2010–2015);
3. Update of training activities and improvement of human resource management in the hydro-meteorological services (2010 to 2012); and
4. Development of market-oriented information services of hydro-meteorology and climate change (2012 to 2014).

The improvements in the capacity of NCHMF capacity are expected to reduce storm-related causalities and property damage. As an example, the significant reduction in the number of storm-related fatalities in the United States can be credited to the improved accuracy of the country's storm forecasts (Lindell, Prater, and Peacock 2007; Willoughby, Rappaport, and Marks 2007). In Vietnam, a case study conducted in Central Vietnam have shown that the damage caused by a storm in 2006, as compared with that caused by a storm event in 1985, significantly decreased due to more accurate and timely warnings (Huy 2009).

One important consideration of the Government of Vietnam in the implementation of these programs is the funding source; these modernization projects require a substantial investment. The total cost of the first two programs identified above is estimated to be about VND 3,456 billion (~USD 167 million), which is 17 times higher than the annual government budget allocation for NHMS of approximately VND 200 billion. In recent years, the Government of Vietnam has faced major reconstruction funding gaps in the aftermath of a disaster; it is then expected that such gaps will be much higher for future major disasters (Wang, Mahul, and Stutley 2010). If these programs are to be implemented, the Government of Vietnam would have to find additional funding source from external financial institutions, such as international funding agencies, in order to adapt to climate change. Accordingly, reliable information on the benefits of improved early warning services for extreme weather events, particularly storms, would play an important role in a cost-benefit analysis of these programs. Such information will assist the government in negotiating for funding from international funding agencies in order to support the country's climate change adaptation projects.

1.2 Significance of the Study

Over the past century, virtually every country in the world has committed significant resources for the establishment and operation of its national meteorological service (NMS). The benefits derived, in terms of increased community safety and well-being, are accepted as self-evident to justify the public expenditure involved. With increasing pressures on national budgets, however, governments in many countries are now seeking more formal demonstration of the benefits of public funds invested in NMS (Freebairn and Zillman 2002a). The results of this research will be useful for Vietnam policy makers in determining the efficiency of the government budget invested in NHMS.

External funding resources are important in assisting developing countries like Vietnam to adapt to the adverse impacts of climate change. However, the funds available are limited relative to the need (Francisco 2008). Both the Government of Vietnam and international donors need the supporting information to ensure the best use of limited funding resources. The results of this research will provide helpful information that will support their funding negotiations for climate change adaptation. Since the poverty density in the coastal areas of Vietnam is high (PEP 2008), the beneficiaries of these successful negotiations would be the poor people; they are the most vulnerable to the extreme climatic events, and they highly depend on external resources for climate change adaptation.

This study used Choice Modelling (CM), an advanced stated preference method, to provide information about the benefits of improved early warning services for storms in Vietnam. Revealed preference methods are particular to specific users and existing goods or services; stated preference methods are more applicable to situations where the good or service is improved to a new stage, and is then offered to a cross section of different users (Rollins and Shaykewich, 2003).

In recent years, a number of applications of the contingent valuation method (CVM)—the most common stated preference method—have been conducted in meteorological valuation (Freebairn and Zillman, 2002a). However, CVM has been widely criticized due to the range of potential estimation biases that can arise from using the method. Alternatively, CM seems to provide a number of advantages over CVM. Using the CM method enables the researcher to have a richer data set, a means to test for internal consistency and to control for framing effect, and it has the potential for benefit transfer (Adamowicz et al. 1998; Bennett and Blamey 2001; Hanley, Mourato, and Wright 2001; Jin et al, 2006; Mogas, Riera, and Bennett 2005; Rolfe and Bennett 2006). Likewise, CM is a useful tool when valuing a multi-attribute public good (Bateman et al. 2008; Hanley, Mourato, and Wright 2001).

In recent years, the applications of CM have rapidly increased (Bateman et al. 2009; Hoyos 2010). To the knowledge of the author, three empirical studies have applied CM for the economic valuation of meteorological services (Brown 2002; Lazo and Chestnut 2002; Lazo et al. 2010). For the valuation of improved storm forecasting, Lazo et al. (2010) concluded that CM is the appropriate method for their future research.

The application of CM in this research provided not only the average value of willingness to pay by the users, but also the marginal values for improving the attributes of storm early warning service. These marginal values can be used to derive values for specific improvement programs that will improve these attributes. Hence, this research can provide more information to support the decision-making process of both the Government of Vietnam and international donors.

As to the knowledge of the author, no CM study has been applied to meteorological valuation in developing countries. The results of this research will provide not only the transferable benefits of improved storm early warning service, but also the research experiences applicable to other countries experiencing a similar situation as Vietnam.

1.3 Research Objectives

The general objective of this research is to provide information on the benefits of improved storm warning service provided by NCHMF based on the application of CM method as a support to the decision-making process of both the Government of Vietnam and climate change donors. Specifically, this research aimed

1. To estimate the willingness to pay (WTP) of users for the improvement of the storm warning service;
2. To derive marginal values for improving the attributes of this service; and
3. To analyze the factors (e.g., income, gender, age, education) affecting WTP and the marginal values.

2.0 METHODOLOGY

2.1 Theoretical Framework of Choice Modelling

CM has its roots in conjoint analysis where individuals make choices between multi-attribute goods and services (Adamowicz et al. 1998; Adamowicz, Louviere, and Williams 1994; Alriksson and Öberg 2008; Boxall et al. 1996). In a CM survey, individuals are requested to decide over a series of choice sets. Each choice set includes a number of alternatives, which are described by different levels of the attributes or characteristics of the good or service that is being valued. In choosing between the alternatives, the individuals also make a trade-off between the levels of the attributes. If a monetary (cost) attribute is included in the choice sets, then the researchers can estimate the individual's marginal WTP for a change in each of the other nonmarket attributes.

CM is an application of Lancaster's theory of value combined with random utility theory (Hanley, Wright, and Adamowicz 1998; Wang et al. 2007). According to Lancaster's theory, individuals' choices are determined by the utility or value derived from the attributes of the goods and services rather than directly from the goods and services themselves (Lancaster 1966). CM is also based on the behavioral framework of random utility theory (RUT), which describes discrete choices in a utility-maximizing framework. Researchers are able to observe only part of individuals' utility, and the unobserved component is randomly distributed. Under RUT, U_{in}, which is the utility that individual n enjoys from choice alternative i, can be decomposed into two parts:

$$U_{in} = V_{in} + \varepsilon_{in} \qquad \text{Equation (1)}$$

where:

V_{in} = systematic and observed component of the choice utility, and
ε_{in} = stochastic unobserved component.

The observed component of the choice utility can be disaggregated further, as utility can depend on the choice attributes (Z_{in}) that may be viewed differently by different individuals and the characteristics of the individual (S_n). Then, Equation (1) can be rewritten as follows:

$$U_{in} = V(Z_{in}, S_n) + \varepsilon_{in}. \qquad \text{Equation (2)}$$

Alternative i is chosen over some other option j if $U_i > U_j$. Due to the unobserved component, the researchers are unable to predict choices perfectly. This uncertainty is expressed in terms of choice probability. The probability that individual n will choose option i over other options j in choice set t is given by

$$Prob(i \mid t) = Prob(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn};\ \text{all } j \in t \text{ and } j \neq i). \qquad \text{Equation (3)}$$

The individual's indirect utility function (V_i) in Equation (2) for a choice option can be modeled with various specifications. Assuming that the relationship between the utility and attributes of the choice is linear such that $V = \beta Z_{in}$, and assuming that only the main effects are considered, the functional form of the indirect utility function is as follows:

$$V_{in} = \beta_i + \Sigma_k \beta_k Z_{kn} + \Sigma_p \theta_p S_{pn} \qquad \text{Equation (4)}$$

where:

β_i	=	vector of constant terms (alternative specific constants) for i = 1,…, I choice options;
β_k	=	vector of coefficients attached to the vector of attributes (Z_{kn}) for k = 1,…, K; and
θ_p	=	vector of coefficients attached to the vector of respondent's characteristics (S_{pn}) for p = 1,…., P.

The utility function estimated for each alternative, therefore, contains a unique alternative specific constant (ASC), the effects of a choice's attributes, and the individual's characteristics. The ASCs represent the average effect on choices of any variation that cannot be explained by the observed attributes or the socioeconomic characteristics.

With the assumption of linear indirect utility function, compensating surplus (*CS*) welfare estimates may be obtained in the following formula (Hoyos 2010):

$$CS = -\frac{1}{\alpha}[\ln \sum expV_{0n} - \ln \sum expV_{1n}] \qquad \text{Equation (5)}$$

where:

α	=	marginal utility income (represented by the β coefficient of the cost attribute), and
V_{0n}, V_{1n}	=	indirect utility functions before and after a specified change in the nonmarket good or service, respectively.

The marginal benefit of an improvement on a single attribute can be estimated by the ratio of coefficient given in Equation (6) (Hanley, Mourato, and Wright 2001):

$$marginal\ WTP = -\left(\frac{\beta_{attribute}}{\beta_{cost}}\right). \qquad \text{Equation (6)}$$

The above ratio is usually known as the implicit price of the nonmarket attribute. It shows the trade-off made between the nonmarket attribute and the cost attribute; it also shows an estimate of the individual's WTP for a unit change in the nonmarket attribute (Bergmann, Hanley, and Wright 2006).

2.2 Survey Design

2.2.1 Determination of attributes and levels

In this study, attributes were used to describe the storm early warning service to the respondents. For the estimated utility function of users, the attributes were the observed independent variables.
The appropriate selection of attributes is a critical component in a CM exercise, since the selected attributes affect *n* respondents' choices, as well as the policy under concern. Having defined the attributes, the levels of these attributes must be determined. Levels can be expressed qualitatively or quantitatively, and the quantitative attributes can be presented in absolute or relative terms (Bennett and Blamey 2001). In this part of a CM exercise, a series of focus group studies should be conducted with the aim of selecting the relevant attributes and levels (Alpízar, Carlsson, and Martinsson 2001). The focus studies could be in the form of verbal group discussion or actual surveys. In order to obtain contrasting opinions and to obtain a representative sample of the population, the focus group composition should be heterogeneous in terms of occupation, background, age, and gender (Suh 2002).

The most notable disadvantage of CM approach is the cognitive burden associated with making choices between bundles of attributes and levels. The larger the number of attributes and levels are, the bigger the cognitive burden that the respondents would face. At this stage of the survey design, this can be solved by carefully selecting the attributes, and then choosing the optimal number of attributes (De Shazo and Fermo 2002). One important lesson, learned from reviewing the previous studies, is that most CM studies in environmental and meteorological valuation use 4–5 attributes, including the cost attribute in each choice set.

Following the above instructions and lessons from the literature, this research started by studying the attributes and attribute levels that had been used in previous studies. There are three CM applications in the valuation of meteorological services, one of which estimated the value of improved storm forecasting in the United States (Table 1).

Table 1. Attributes in the previous CM studies

Author	Value	Site	Attributes
Brown (2002) as cited in Gunasekera (2004)	Value of public weather forecast services	Ontario, Canada	Forecast length Frequency of updates Geographical coverage A change in annual federal income taxes
Lazo and Chestnut (2002)	Value of current and improved weather forecasts	Nine cities across the United States	Frequency of updates Accuracy of one-day forecasts Accuracy of multi-day forecasts Geographic detail of forecasts An increment to annual taxes
Lazo et al. (2010)	Value of improved hurricane forecasting	Miami, Florida, United States	Accuracy of predicting location of landfall Accuracy of predicting time of landfall Accuracy of predicting maximum wind speed Accuracy of predicting storm surge An increase in the current level of taxes

The attributes used should be relevant to policy makers and the policy under concern (Bennett and Blamey 2001). One of the specific objectives stated in the Strategy for Development of Hydro-meteorological Service of Vietnam is to improve the accuracy levels of the country's storm forecasts to be comparable to that of the Japan Meteorological Agency. From the policy makers' viewpoint, accuracy is a key attribute of an improved storm warning service.

The Strategy also suggests that an important measure for the development of the hydro-meteorological service in Vietnam is to carry out the market-oriented information services of hydro-meteorology and climate change. Given the budgetary pressures faced by many countries, it is necessary to supplement traditional public funding with revenues obtained from commercial meteorological activities. Many NMSs now depend on fees for services as part of their income, with up to 40% or more in some countries (Freebairn and Zillman 2002b).

In Vietnam, the idea of introducing the market-oriented services has been applied since 2008, the year that NCHMF introduced Short Message Service (SMS) Weather services. The SMS Weather service includes three types of services: SMS on weather forecasts, SMS on storm, and SMS on tropical depression. To receive information on weather forecasts at a desired place, current storm, or current tropical depression, users in Vietnam can send an SMS with specific designed contents to the service number 8253. The desired information will then be sent back to the user's mobile phone. Each SMS provided by the SMS Weather services has a fee of VND 2,000. According to a report of NCHMF, by the end of 2008 and by early 2009, the SMS Weather service had the highest number of users (about 100 messages per month). After a few months, however, the number of messages gradually decreased to about 20 messages per month. As per the author's knowledge, the SMS weather services have been closed for improvement since December 2009. Hence, it is important to know whether the SMS weather service should be improved and to what extent and nature of improvement should be made. These SMS services are, to date, unique commercial services introduced to the general users. The information about the WTP for an improved SMS warning service will be very helpful for the development of other commercial meteorological services that will be provided to the public in the future. From the viewpoint of policy makers, developing new dissemination platforms, such as mobile phone short messages, for the improved storm warning service is also a relevant attribute.

Considering that more and more people are getting access to mobile phone network services (even in the rural areas), mobile phone short message warnings will provide a timely dissemination of storm information in Vietnam in the future. According to a national census conducted by the Ministry of Information and Communication (MIC) in June 2010 with regard to Vietnamese's use of phone and internet service, only 0.44% of the total villages do not use mobile phones, while 30 million people (38% of population) use mobile phones. The use of a mobile phone to collect storm information may be more prevalent at the household level. The number of households having mobile phone users is useful data for assessing the potential of the mobile phone short message warning for storms. From the full sample of this research's survey and the sample of the MIC's national census, it is estimated that each household in Vietnam has 2.34 mobile users, and the number of households with mobile phone users are nearly 13 million households (30 million users divided by 2.34 mobile users per household), which accounts for 64.4% of the total households in Vietnam. In rural areas, this ratio of the household with mobile phone users is estimated at 62.6%.

Aside from the concern over the people living in rural areas, there is also a question whether fishermen can access mobile phone network to know if they can use the mobile phone short message warning or not. Since August 2011, Viettelmobile, a telecom service provider in Vietnam, has provided a prepaid service called "Sea+" for people in coastal and sea areas.[1] The target users of the Sea+ package are fishermen working at sea. The "Sea+" package shows that the mobile phone network is accessible for Vietnamese fishermen. Besides, when the focus studies and surveys were being conducted in the coastal areas, the author asked fishermen if they could use the mobile phone short message warning. Most of the fishermen answered that they could access the mobile phone SMS service while at sea. For those working offshore and are outside the mobile phone networks, they have Icom devices, which can be used to contact their relatives who are living in coastal areas and can access mobile phone network. It can be concluded that most of the fishermen are able to access the mobile phone network, and it is possible for them to use the mobile phone short message warning for storm warnings.

However, it is not possible to transmit automatically a storm warning SMS to mobile phone users, who could potentially be affected by storms, based on their billing address. Most mobile phone users in Vietnam are prepaid users who don't have to register their billing address. Mobile phone users who want to receive storm information have to send an SMS to a designated central number, and then an SMS that gives current storm information will be sent back to mobile phone users. Mobile phone SMS is clearly a private good, but the program of improving storm warning service is a public good. To be consistent with the frame of the improvement program, the attribute of mobile phone short message warning in this study was valued as a public good. The storm warning SMS service was presented to respondents as a freely accessed service for every mobile phone user.

Aside from the attributes of accuracy and new dissemination platforms, the attribute of frequency of update also appears to be relevant to policy makers in Vietnam. The early warning service for storm in Vietnam is administered by the Prime Minister's Decision of the Regulation on Tropical Depression, Storm, and Flood Forecasting. The frequency of updates for storm warnings is set by the Regulation. In recent years, the number of updates per day has shown an increasing trend (Table 2).

Table 2. The frequency of update for storm warnings in Vietnam

Category of Warnings	Regulation on Tropical Depression, Storm, and Flood Forecasting		
	In 2005	In 2006	In 2011
Warnings for storm outside the East Sea	2	2	4
Warnings for storm inside the East Sea	4	8	8+*
Warnings for nearby storm	7	8	8+*
Urgent warnings	8	8	8+*

Note: *In addition to eight main bulletins per day, NCHMF may issue some additional bulletins if necessary.

Based on the previous CM studies and the above discussions on the Vietnamese policy makers' requirements for improved storm warnings, a list of relevant attributes was developed in this study and is presented in Table 3.

[1] The details of Sea+ service can be found at the website of Viettelmobile (http://www.viettelmobile.com.vn/di-dong/goi-cuoc-sea/gioi-thieu-goi-cuoc-10.html, accessed on 23/11/2011).

Table 1. The attributes relevant to the improved storm warning service in Vietnam

Attributes	Notes
Accuracy of projected landfall	Measured by the mean errors of center position forecast
Accuracy of forecast storm intensity	Measured by the mean errors of maximum wind speed forecast
Accuracy of time of expected landfall	Measured by the mean errors of landfall time forecast
Accuracy of forecast storm surge	Measured by the mean errors of storm surge forecast
Mobile phone SMS warning	In addition to the traditional disseminating platforms (i.e., TV, radio, loudspeakers, etc.), a new platform could be mobile phone SMS.
Frequency of update	Measured by number of updates per day
Forecast length	Measured by number of forecast days

The attributes of a storm warning system should also be relevant to the users. In August 2010, the researcher conducted a focus study through an internet survey in order to collect users' opinions on what attributes of a storm warning system they would be interested in. An email invitation with a link to the online questionnaire was sent to the author's friends, who in turn forwarded the invitation email to other potential participants based on their contacts in Vietnam. The invitation was also posted on some online Vietnamese forums to request the participation of the forums' members. The voluntary respondents completed the online questionnaire.

To reduce the ordering effect, in which an attribute placed at the first order of the list may gain more attention than an attribute at the last order, the attributes presented in Table 3 were randomly ordered in the online questionnaire, and their orders were changed twice during the survey. With 122 responses, Figure 5 presents the user's priority for the attributes of improved storm warning service in Vietnam. The users considered the accuracy of forecast information (i.e., the location and timing of landfall) as the most important attribute of an improved storm warning service. It also shows that more than 90% of respondents chose "accuracy of projected landfall" and "accuracy of time of expected landfall" as the important components of an improved early warning service for storm. Most respondents did not select "accuracy of storm surge forecast" due to the strong causal relationship between storm intensity and storm surge.

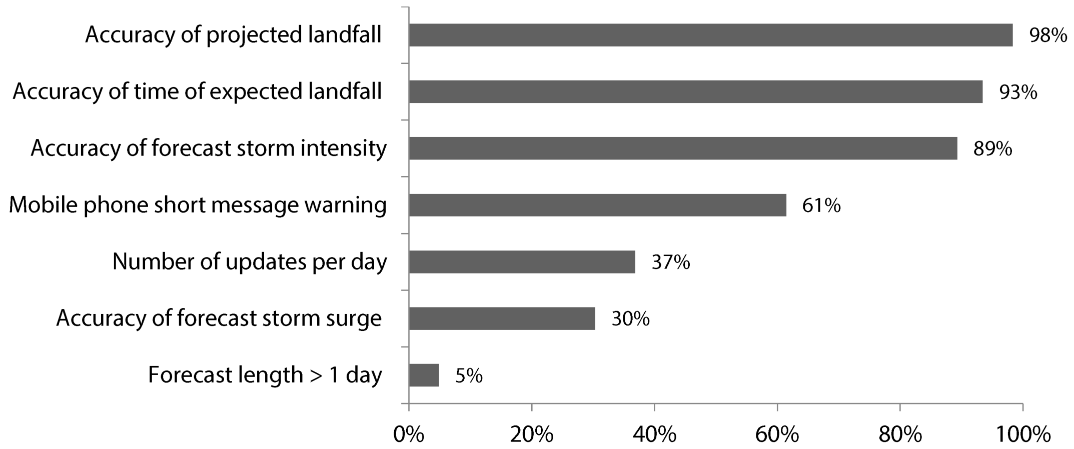

Figure 5. Priority for attributes of improved storm warning service in Vietnam

However, the internet focus study had some weaknesses in its sampling procedure; it was conducted based on the contacts of the author, whose home town is in Northern Vietnam. Thus, most of the respondents also live in Northern Vietnam (Figure 6) when most of the vulnerable communities are in Central Vietnam. Likewise, most of the people who have internet access are young and living in urban areas. Thus, the respondents in this internet survey were young with an average age of about 28 years old. Compared with the older people, the young respondents did not have much experience on storm risk and on the usefulness of a storm warning service.

To solve the sampling weaknesses of the internet focus study, another focus study was conducted. In December 2010, the researcher conducted face-to-face interviews in some of the coastal areas in Central and Northern Vietnam. This face-to-face survey had 52 respondents who were living in rural and urban areas.

Instead of presenting a prepared list from where the respondents could choose their relevant attributes from, the author asked the respondents a question "Which information in a storm warning bulletin have you collected in order to prepare for an approaching storm?" This approach helped to avoid the ordering effect and to elicit the most relevant storm information from the respondents' memory.
Most respondents used the information on projected location of landfall, storm intensity, and time of landfall for their decision making (Figure 7). The information about storm location was the most important to the users, particularly if the storm is projected to affect their area. Some respondents indicated that they would continue to consider the other information on intensity and time of landfall in order to make decisions about storm contingency plans (such as changing their work schedule, strengthening their house, evacuation). The respondents gave highest priority to the information on storm position. The priorities of information given by the respondents in the latter focus study were consistent with that of given in the earlier internet focus study. The only difference was that in the latter study, the information about storm intensity had a higher priority than the information on time of landfall. This may be because in a storm forecast bulletin, the information on storm intensity is presented twice in the current and projected status of the storm, whereas the time of landfall appears only once in the projected information of storm.
The information on intensity may be easier for the users of storm warning service to remember.

Although storm warnings contain some specific storm information that is important to the users, accurate storm forecast should be presented to the respondents as one package. Several projects are currently being implemented toward this end in the Strategy for Development of Hydro-meteorological Service. Accordingly, the improvements in the forecast systems (modelling, technical systems, and human capacity) currently being undertaken by NHMS will enable the agency to deliver a more accurate set of information for the whole storm forecast, and not just improve the accuracy of individual or specific components of the storm forecast.

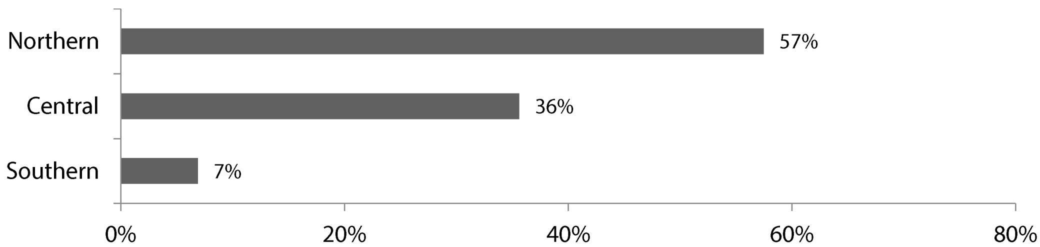

Figure 6. Locations of respondents of the internet focus study

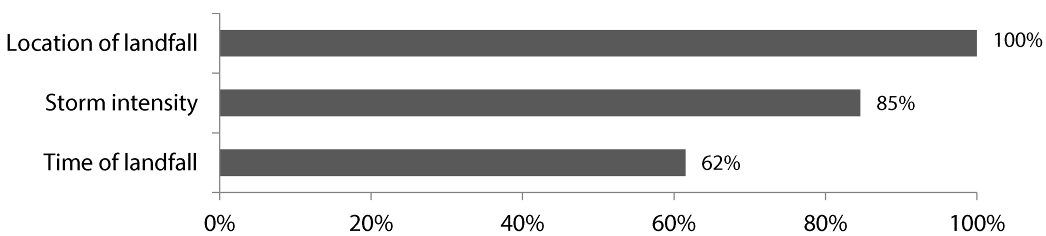

Figure 7. Priority for storm information collected to prepare for an approaching storm

In developing countries where meteorological database is usually limited, it is difficult to measure by how much each storm forecast component needs to be improved in order to achieve the target accuracy level for each information component. The varying accuracy levels of each component of the storm forecast not only put a cognitive burden on the respondents, but may also prove to be of little use to policy makers. The accuracy attribute in this study, therefore, was introduced to the respondents as a single package, which included accuracy of forecasted position of the storm and accuracy of the expected time of landfall. The accuracy of storm intensity was not included among the choices; it is technically difficult to improve the accuracy of storm intensity forecast. In the last 10 years, the storm forecast verifications that the United States National Hurricane Center and the Japan Meteorological Agency have provided have shown no or little improvement in terms of the accuracy of their storm intensity predictions. Thus, excluding this attribute makes the improvement scenarios more realistic; it also reduces the cognitive burden on respondents.

The results of the focus survey indicated that users of the storm warning service in Vietnam prefer to update the storm information they get. Many respondents in the face-to-face focus survey stated that they frequently used the early warning service to update their storm information in case of a storm event. About 44% of the respondents listened to the radio every hour in case of nearby storms. The reason that they preferred to be frequently updated was because of the composition of the storm warnings, which include the current status of storm (position, intensity) and the projected information of storm. Getting more updates means that users acquire newer information about the current status of storm, which accordingly helps them to keep track of the storm. The updated information on the current status of storm will also be useful for those users who had experienced previous storms and wanted to make their own prediction in addition to the forecast of the early warning service.

All the information mentioned helped to determine the attributes presented in Table 4. The accuracy attribute was presented as Improvement Levels 1, 2, and 3 relative to the current condition. The researcher conducted personal interviews to help respondents understand the levels of accuracy attribute. The detailed descriptions of the levels are elaborated in Table 5. In Table 5, the forecast error levels in the current condition (the status quo) were determined based on the results of the consultations and interviews conducted by the researcher with experts, since there was no official report that verifies the accuracy of storm forecasts in Vietnam. The improvement levels were then selected based on the findings after the researcher examined the possible improvement levels from some developed countries (i.e., US and Japan) and on users' expectation as expressed in the focus studies.

The forecast error of the storm position was based on that of the central position, which is estimated at 140 km in the 24-hour forecast in Vietnam. This error level means that if an approaching storm is predicted to make landfall at a particular location (described by a house symbol), then the actual area of landfall can be somewhere within the 140-kilometer radius of the projected area of landfall (described by the dark range around the house symbol). It also means that the people living at a location less than 140 km from the predicted area of landfall would still have to worry whether the storm will make landfall in their location or not. If the improvement level is Level 1, in which the forecast error of the storm position is 100 km, people living at a location more than 100 km from the predicted location of landfall can be assured that the storm will not make landfall in their location. The gap of 40 km between the Status Quo Level and Improvement Level 1 was selected because the eye of a storm (an area at the center of a storm) is a roughly circular area with a typical radius of 15–30 km. Improvement Level 1, therefore, is expected to be a meaningful improvement for the respondents in terms of storm risk. Improvement Level 3 has an issue of technical feasibility. The error level of the storm position forecast at Improvement Level 3 is 60 km; this may be technically feasible in the future considering that the United States National Hurricane Center has been using the forecast error level of 74 km since 2010.

Table 4. Attributes and levels

Attributes	Current Levels	Improvement Levels
Accuracy of storm forecast	Current condition	Level 1, Level 2, Level 3
Number of updates per day (times)	8	8, 12, 16
Mobile phone short message warning	Not available	Not available, Available
A one-off payment in your electricity bill (in '000 VND)	0	50, 150, 250

Table 5. Description of "accuracy of storm forecast"

A storm forecast contains two main components of projected information: storm position and time of landfall.

The storm position forecast helps to determine "whether the storm would move toward your place or not."

The time of landfall forecast helps to determine "when you need to do the preventive activities."

A more accurate forecast information means that the margin for error is smaller (or the dark ranges in the below table), which can help reduce damages due to storm in case storms affect your place; it also helps avoid incurring costs for unnecessary preventive activities when the storm will not actually affect your place.

		Forecast Error of STORM POSITION	Forecast Error of EXPECTED TIME OF LANDFALL
Current condition		140 km / 140 km	Before 6 hours / After 12 hours
Improvement Levels	Level 1	100 km / 100 km	Before 4 hours / After 8 hours
	Level 2	80 km / 80 km	Before 3 hours / After 6 hours
	Level 3	60 km / 60 km	Before 2 hours / After 4 hours

Regarding the forecast errors of the expected time of landfall, the current level is "6 hours before and 12 hours after (–6, +12) hours," which has the mean absolute landfall time error of eight hours with a three-hour early bias. The early bias resulting in the uneven range of landfall time error is consistent with conservative forecasts in order to account for the possibility that the storm would accelerate; people should then have storm-risk mitigation measures well in advance by then (Powell and Aberson 2001). To help the respondents understand the forecast errors of the expected landfall time, specific examples were used. The current level of (–6, +12) hours means that if the time of landfall forecast is at 11:00 a.m., then the actual time of landfall can be from 05:00 to 23:00. If the improvement level is Level 2, which is (–3, +6) hours, people can begin taking precautions, like stop working, within only 9 hours (from 6:00 to 15:00) instead of 18 hours (from 05:00 to 23:00) as was the situation before the proposed improvement. Regarding Improvement Level 1, the time error of (–4, +8) hours was selected, since the forecast verification of the India Meteorological Department (IMD) in 2009 showed that the mean absolute landfall time error had been six hours. In the forecast verification of IMD, the minimum value of the time forecast errors were two hours early (for storm WARD) and four hours delayed (for storm AILA). The time errors of (–2, +4) hours at Improvement Level 3 seem technically realistic.

Not only would the more precise forecast information help in reducing damage due to storms, it would also help in avoiding the costs of unnecessary preventative activities. The visual aids in the description would help respondents easily understand the higher levels of improvement, specifically, the range of errors (or the dark areas) is smaller and the forecast information is more exact. In Table 4, the improvement levels of the frequency of update are 8, 12 and 16 times per day. It is technically feasible to provide updated storm information 16 times per day. In Australia, when an approaching cyclone is under radar surveillance, storm warnings can be issued hourly (24 times per day). Meteorological experts in Vietnam also confirmed the feasibility of the frequency of updates suggested in this study.

A pilot survey (with 58 respondents) was conducted to check whether the proposed attributes of an improved warning service were acceptable. The analysis of the pilot survey showed that all attribute variables had the expected signs, and the coefficients on accuracy increased as expected (Table 6).

Table 6. Results of Conditional Logit Model for the pilot survey

Variables	Descriptions of Variables	Coefficient	Standard Error
A_Level 1	Accuracy of Improvement Level 1	0.50111	0.3253
A_Level 2	Accuracy of Improvement Level 2	0.69104**	0.3446
A_Level 3	Accuracy of Improvement Level 3	0.95277***	0.3351
Update	Number of updates per day (times)	0.09964**	0.0398
Mphone	Mobile phone short message warning	0.45197***	0.1339
Cost	An one-off increase in electricity bill (in '000 VND)	–0.01697***	0.0020
Log-likelihood values		–178.9690	
Pseudo-R^2		0.24912	
N		346	
N		346	

Note: ***, ** refer to values that are significant at 1% and 5% levels, respectively.

Another test to check the forecast attributes was done on the data of the final survey. The design of the questionnaire allowed choice tasks to be presented in a random order to avoid the ordering effect. This means that in the first question on choice tasks, different choice sets were offered to the respondents. If only the responses to the first question would be used for data analysis, then the issue of learning effect would be removed. The learning effect is a common sequence of events for a respondent in a choice task: (1) the respondent may learn about the task and the effort necessary to accomplish the choice task by trying out different strategies for some number of replications, followed by (2) the application of the learned behavior during another number of replications.

In Table 7, the coefficients of the accuracy levels increase as the improvement levels increase. The other attribute variables have the expected signs. Without the learning effect, the respondents appeared to have understood all the attributes. Hence, the attributes would be meaningful to the respondents. The selection of the attributes seemed appropriate.

To estimate the WTP and marginal values of a change in each of these attributes, a cost attribute or payment vehicle was included in the choice sets. To the knowledge of the author, most previous stated preference studies conducted in Vietnam had used the electricity bill as the payment vehicle, because it is mandatory and has good coverage (Do and Bennett 2008; Hoa and Ly 2009; Thuy 2008). One-off coercive payment through the electricity bill, therefore, was selected as the payment vehicle in this study. In the main survey, only seven respondents, accounting for 5% of those who did not support the improvement program, did not agree on adding the payment to their electricity bill. The payment through an increase in electricity bill appeared acceptable in Vietnam.

The one-off payment was selected because the Government of Vietnam is sourcing financial investment to finance the improvement programs stated in the Strategy for Development of Hydro-meteorological Service. A characteristic of information is that when information is available, it is relatively cheap to maintain. The marginal costs (i.e., additional operating costs) of the improved early warning service (which provide storm forecast information) will not be much larger than the current operational costs. The long-term operational costs of the improved service, therefore, will not be a matter of concern. In addition, the annual fee will put a cognitive burden on the respondents. When faced with an annual fee, a rational respondent will have to think about a discount rate, and then use the rate to calculate the present value of the total amount that he/she will pay. In this CM study, there were three levels of the cost attribute, which means that the respondent would have to do the above calculations three times. To avoid this source of cognitive burden, a one-off payment was appropriate for this research.

In order to determine the acceptable levels of the cost attribute, the respondents in the focus studies were asked about their maximum WTP for an improved early warning service for storms. In their responses, the value offered most frequently was VND 100,000. Based on the focus studies, three levels (i.e., VND 20,000; VND 100,000; and VND 200,000) were first proposed for the cost attribute. However, in a pretest survey conducted in July 2011 on 170 respondents, 12% of the respondents stated that they had ignored the cost attribute when considering the choice sets. This indicates that the cost levels were too low. If cost values are too low, then they are ignored; little useful information can then be extracted from the choice sets. Thus, the cost levels were raised in the main survey (i.e., VND 50,000; VND 150,000; and VND 250,000). In the main survey, only 4% of respondents stated that they had ignored the cost attribute when making their choices. The cost levels used in the main survey were sufficiently high to catch the respondent's attention, and the highest level of VND 250,000 was expected to choke off demand for the service involved.

Table 7. Results of Conditional Logit Model for the first question in the final survey

Variables	Descriptions of Variables	Coefficient	Standard Error
A_Level1	Accuracy of Improvement Level 1	1.42698***	0.2154
A_Level2	Accuracy of Improvement Level 2	1.63421***	0.2290
A_Level3	Accuracy of Improvement Level 3	2.28684***	0.2595
Update	Number of updates per day (times)	0.02031	0.0232
Mphone	Mobile phone short message warning	0.23765***	0.0724
Cost	An one-off increase in electricity bill (in '000 VND)	–0.01413***	0.0010
Log-likelihood values		–571.5489	
Pseudo-R^2		0.18489	
N		1,014	

Note: *** refers to values that are significant at 1% level.

2.2.2 Experimental design

Once the attributes and levels had been determined, an experimental design was used to construct the choice sets that would be presented to the respondents. The primary question for the experimental design was "How can the attribute levels be best allocated to the profiles of alternatives, and how can the profiles be then combined into the choice sets?"

To solve this question, as a starting point, the researcher used a computer software to design a full factorial that contained all possible combinations of the attributes with various levels. A full factorial is, however, very large and not manageable for individual respondents. Therefore, most researchers rely on fractional factorial designs, which consist of a subset of the full factorial. The most well-known fractional factorial design type is called the orthogonal design; this aims to minimize the correlation between the attribute levels in the choice sets. More recently, some researchers have suggested another type of fractional factorial designs, or the so-called efficient designs (Bliemer and Rose 2010; Bliemer, Rose, and Henser 2009; Huber and Zwerina 1996; Rose and Bliemer 2009; Sándor and Wedel 2001). The efficient designs do not merely try to minimize the correlation in the data for estimation purposes, but also aim to provide data that generate parameter estimates with as small as possible standard errors. In order to achieve the goal of efficiency, these designs essentially try to maximize the information from each choice set.

Efficient designs seem to outperform the orthogonal designs in terms of statistical power. With efficient designs, more significant parameter estimates can be achieved with an equal or lower sample size (Rose and Bliemer 2009). The reason for this is that orthogonal designs are generated primarily to satisfy the econometric properties of linear regression models, while the discrete choice models (i.e., logit or probit models) are not linear. The efficient designs are generated in such a way as to tie the design to the econometric form of the discrete choice models; these designs are constructed with the aim of minimizing the predicted standard errors of the parameter estimates, and hence maximize the t-ratios for each of the parameter estimates for a given sample size. Thus, the generation of more efficient choice designs is primarily relevant to studies involving small finite samples. The aim of such designs is therefore to produce statistically significant parameter estimates given a small sample as possible. If sample size is not an issue, then the orthogonal designs may be easier to implement or otherwise more appropriate (Rose and Bliemer 2009).

However, using efficient designs requires attention to a number of issues as follows:

1. First, the generation process requires prior knowledge of parameter estimates. Although the prior information may come from previous studies, focus groups, or pilot studies (Carlsson and Martinsson 2003; Huber and Zwerina 1996), the uncertainty surrounding the assumptions about the parameters has been somewhat controversial. Using Bayesian prior parameter distributions may help alleviate some of these concerns (Sándor and Wedel 2001); however, the computation time can be an issue, especially when the complicated discrete choice models (i.e., mixed logit model) are involved.
2. Second, the efficient design is specifically optimized to the econometric model assumed. This issue requires advanced knowledge of the model to be estimated. Some researchers have shown that designs that are optimized for the conditional logit model, which is a standard multinomial logit model, may not necessarily be optimal if later estimated using other model forms (i.e., the nested logit or mixed logit model) (Bliemer and Rose 2010; Bliemer, Rose, and Henshher 2009; Sándor and Wedel 2002; Yu, Goos, and Vandebroek 2009).

With regard to the experimental design of this research, the orthogonal design seemed more appropriate since it does not depend on prior knowledge of the parameter estimates. In order to have a representative sample of the Vietnam population, the survey sites should be in both Central and Northern Vietnam. Selecting survey sites in both Northern and Central Vietnam would also help facilitate the implementation of a validity test in the form of a comparison between responses from the Northern region and from the Central region. The respondents living in the Central Vietnam are exposed to higher risk of storm; thus, they are expected to have a higher WTP for the improvement of the storm early warning service than those from the Northern region. The preliminary results with the statistical significance of "Central region" variable showed that the Central Vietnam respondents had significantly higher WTP than the Northern Vietnam respondents did. An efficient design relying on prior parameters estimated from a pilot survey in the Central region would not be appropriate to elicit the true preference of respondents living in the Northern region. The prior knowledge of parameters based on mixed responses of the Central and Northern Vietnam respondents may not be suitable to the design choice sets presented to the respondents living in Central Vietnam or in Northern Vietnam. This problem of selecting appropriate prior parameter values can be solved by applying the sequential efficient designs (Bliemer and Rose 2009; Scarpa, Campbell, and Hutchinson 2007), in which the efficient design for the Central region uses prior values estimated from a pilot survey in the Central region, while the design for the Northern part uses prior knowledge acquired from a separate survey in the Northern region. However, it would be difficult to interpret the difference in the results between the respondents in Central region and the respondents in the Northern part. The reason is that there would be two sources of differences: difference in storm risk and difference in choice sets presented to the respondents living in each region.

In addition to the criterion of orthogonality, the experimental design in this research was also generated with the property of attribute level balance. The attribute level balance property means that each attribute level appears in an equal number of times for each attribute. Having an attribute level balance ensures that the parameters can be estimated over the whole range of levels, instead of only having data points at one or few of the attribute levels. Although imposing attribute level balance may restrict the design to be suboptimal, it is generally considered a desirable property (Rose and Bliemer 2009).

The main effect orthogonal design was applied in this research in order to generate 24 choice sets. To reduce the cognitive burden, each respondent was randomly chosen to face a block of six choice sets. Figure 8 presents an example of a choice set.

In each choice set, the respondents indicated their preference between two alternatives: one potential improvement program and the status quo (i.e., keeping all levels at their current levels). In experimental designs for CM, an increasingly popular design is the three-alternative choice task, in which respondents are asked to select one of two alternate management states or the current situation. The statistical models estimated from three-alternative choice sets are more efficient than those from two-alternative choice sets (Rolfe and Bennett 2009). However, this can come at a cost of requiring considerable cognitive effort by respondents who are not familiar with the type of CM questions, which includes people living in rural areas of developing countries. The two-alternative choice sets seem simpler to handle for the target respondents of this research. Besides, in the case of public goods (i.e., improvement of early warning service for storm), the voting games offered by the two-alternative choice design can be easier for the respondents to understand, since the voting games are similar to multi-candidate elections in the respondents' real lives. The design of two-alternative choice sets, therefore, was applied in this research.

	Current Situation	Proposed Improvement
Accuracy of storm forecast (STORM FORECAST / STORM PREPAREDNESS)	Current condition	Improvement **LEVEL 2**
Number of **updates** per day (NEW!)	8 times	**16 times**
Mobile phone short message warning	Not available	**Available**
A **one-off payment in your electicity bill**	None	**150,000 VND**

Figure 8. An example of choice set

Any improvement program was described through the different improvement levels of the three storm warning service attributes—accuracy of forecast information, number of updates per day, and mobile phone short message warning—as well as increased payment in electricity bill of the household. The improvement levels of the accuracy attribute were Level 1, Level 2 and Level 3. Each improvement program thus represented an improvement in accuracy over current (baseline) forecasts. Little information can be learned by a choice set that asks a respondent whether they prefer a program with no improvement in accuracy of forecast information if the improvement in accuracy is the most expected attribute of an improved early warning service. Besides, this design of the accuracy attribute seems to be more realistic. The Vietnamese Government's Strategy has the specific objective of improving storm forecast accuracy; one proposed improvement program is to modernize forecasting technologies and monitoring systems for hydro-meteorological services in 2010–2012. This was approved in June 2010. It was expected that the investment in forecasting technologies and monitoring systems will improve forecast accuracy.

However, this design of the accuracy attribute would cause a problem in the statistical analysis of this survey. The accuracy attribute should be considered as a qualitative variable; thus, in the utility function, there would be three accuracy dummy parameters representing the four levels of accuracy (including the current situation, Improvement Level 1, Improvement Level 2, and Improvement Level 3). Since the accuracy level in the current situation was designed not to overlap with the improved alternative levels, the accuracy parameters were confounded with the ASC of the status quo. This problem could be solved by excluding one of the three accuracy dummy parameters, and then by taking into account the exclusion in the ASC interpretation.

2.2.3 Questionnaire design

The structure of the questionnaire included the following main components:

1. *Part 1 (Question 1 – 11):* This part of the questionnaire was designed to collect information about the respondents' uses and sources of storm warnings and about their perceptions of current storm warning service and storm risk.
2. *Part 2 (Question 12 – 24):* In this part, the respondents were provided with information about the importance of the storm early warning service. By using show cards, interviewers also introduced the respondents to scenarios for improving early warning service and the corresponding budget constraints. Before making choices in the six choice tasks, the respondents were presented with three examples of choice sets to familiarize them with the choice tasks. The three examples that had three different cost levels (designed to avoid the anchoring effect) suggested that the starting cost level influences WTP estimates.

   The order of a series choice tasks presented to respondents can affect the choice outcomes (Bateman et al. 2008). To avoid the ordering effect, the main choice sets, from which the respondents made their choices, were presented by using show cards; the orders of these show cards varied for each respondent.

   Follow up-questions were included in this part of the questionnaire to enable the researcher to identify if there are anomalies in the responses. These anomalies may include (a) attribute non-attendance (respondents may ignore one or more attributes when making their choices) and (b) hypothetical bias (respondents may agree to pay because the payment is hypothetical).
3. *Part 3 (Question 25 – 41):* This section was designed to collect the respondents' socioeconomic and attitudinal information such that the researcher can determine how well the sample represents the population, and to analyze the factors affecting both the average and marginal WTP for the improved early warning service for storms in Vietnam.

2.3 Survey Implementation

2.3.1 Interviewer briefing

The research team was composed of two groups; each group was composed of five interviewers. One group covered the Central region, whereas the other covered the Northern region. In each region, one-day briefings for the interviewers were held before the surveys. The briefings were undertaken by the author. The interviewers were given the briefing notes as well as the set of questionnaires, show cards, and choice sets.

The briefing was held to ensure that the interviewers knew exactly what the study was about, how they will conduct the interview, and how they would fill in the questionnaire. The briefing took the interviewers through each question of the questionnaire, and all questions from the interviewers were answered thereafter. After reviewing the questionnaire, a practice interview was conducted by all interviewers.

2.3.2 The pilot study

Before the main survey, a pilot survey with 170 respondents was implemented in July 2011. The primary objective of the pilot study was to test the contents and logistics of the survey process. More specifically, the pilot study was done to test the following:

1. Relevance of the attributes and its levels;
2. Readability of the questionnaires in general;
3. Respondents' ability to complete the entire questionnaire;,
4. Correct skips or logic in the questionnaires;
5. Respondents' ability to complete the choice modelling sections;
6. Interviewers' understanding of the study and how it should be administered;
7. Interview length and the number of possible interviews completed in a day; and
8. Efficiency of the interview process.

2.3.3 The main survey

In August and September 2011, face-to-face surveys were conducted in four sites: Do Son district (Hai Phong province), Vinh Quang commune (Hai Phong province), Son Tra District (Da Nang City), and Tam Tien commune (Quang Nam province). These sites represented both the urban and rural coastal areas in Northern (Hai Phong province) and Central (Quang Nam, Da Nang provinces) Vietnam. These sites were also affected by the storms in 2009 and 2010 (Figure 9). In July 2010, Hai Phong was affected by Storm Conson; in September 2009, Quang Nam and Da Nang were affected by Storm Ketsana. Recent memories of the storm effects and experiences on the use of storm early warning service were expected to help respondents provide reliable answers.

The target subsample size in each survey site was 250. There is no existing formula for computing the required sample size in cases of performing stated choice modelling (Bliemer and Rose 2009). Therefore, to determine the target sample size, the author reviewed a number of previous stated preference studies that had been conducted in Vietnam (Table 8).

Figure 9. The provinces (with larger dots) where main surveys were undertaken.

Table 8. Previous studies applying stated preference methods in Vietnam

Attribute	Do and Bennett (2008)	Hoa and Ly (2009)	Thuy (2008)	Tuan and Navrud (2007)
Stated preference method applied	Choice modelling (CM)	Contingent valuation (CV)	CV	CM and CV
Sample size	917	900	800	930 (446 for CM, and 484 for CV)

Do and Bennett (2008) had three main subsamples (conducted in Dong Thap province, Ho Chi Minh City, and Ha Noi City) with the choice structure of five attributes with four levels. The target size of a split sample in the study of Do and Bennett (2008) was 300. The choice modelling in the study of Tuan and Navrud (2007) was conducted with two main split-samples (foreign visitors and local residents) and the choice structure of four attributes with a maximum of five levels. The size of a subsample applied by Tuan and Navrud (2007) was estimated at about 225. This research was conducted in four sites, and its choice structure contained four attributes with maximum of four levels. Applying a split sample size of 250 (which can be considered as a medium size in the range of 225–300), this research with four main subsamples had a total sample size of 1,000 (i.e., 250 x 4). The surveys were conducted using stratified sampling, in which the village was used as the strata. The sampling frames were designed based on the maps provided by the village leaders. The sample units used were households; the unit of inquiry was household members over 18 years old.

The surveys were implemented as a project of the Institute of Strategy and Policy on Natural Resources and Environment (ISPONRE), which is an advisory unit of MONRE for policy and strategy. With recommendation letters from ISPONRE, the survey was supported by the local governments, who provided maps of the survey sites and the contact numbers of the local village leaders. At the survey sites, the village leaders accompanied the interviewers and helped in introducing the survey as an activity of MONRE. The survey was also implemented in close collaboration with NCHMF. The interviewers of the survey were hydro-meteorological staff members who can explain, if required, some of the technical aspects of the storm early warning system to the respondents. With the participation of ISPONRE and NCHMF representatives, the respondents would tend to believe that their survey responses can influence the government's actions in improving the current storm early warning service. The dominant strategy of the respondents, therefore, may be to answer truthfully.

However, employing hydro-meteorological staff members as the interviewers may cause an overstated WTP; the respondents may be overly enthusiastic to look for a positive WTP, which to some extent will be beneficial to them. To reduce the interviewer bias, the author supervised the interviewers at the survey sites, and reminded them not to deviate from the scripts provided in the questionnaire and the show cards. In the data analysis step, dummy variables for each interviewer were used to test the interviewer biases. The results showed that of the total 10 interviewers, 2 interviewers produced significantly higher WTP than the others. Unfortunately, interviewer bias is the potential weakness of face-to-face surveys.

3.0 ANALYSIS AND RESULTS

3.1 Data Description

Hypothetical bias, which leads to the differences between actual and hypothetical WTP, is a well-known problem in stated-preference studies. To reduce this bias, the author applied follow-up certainty scales, which allowed the respondents to indicate their assurance that they would actually pay the amount they had indicated. The certainty scale in this research used a 10-point rating scale with 1 labeled “very uncertain” and 10 labeled “very certain.” Most studies find that a cut-off of either 7 or 8 is needed to equalize hypothetical and actual WTP (Morrison and Brown 2009). In this research, a cut-off rating of 7 was used to produce estimates that were expected to match actual payments. The approach to handle the cut-off certainty rating was to recode the answer to a “No” response when the respondents who had a certainty rating lower than 7 answered “Yes.” (Blomquist, Blumenschein, and Johanneson 2009; Blumenschein et al. 2008; Blumenschein et al. 1998).

The survey had been introduced to 1,133 households, of which 1,014 household representatives agreed to take part in the survey and subsequently completed the questionnaire. Therefore, the response rate was 89%. Table 9 presents the detailed information on the sample size and response rate. In the final survey, 82 respondents, accounting for 8% of the full sample, objected to the choice scenarios. The top reason for rejecting the proposed improvements was that the government is responsible for paying the costs of the improvements (Table 10).

Table 9. Sample size and response rate

Survey Sites	Full Sample	Response Rate	Sample with Certainty Cut-Off Rating of 7	
			Size	Ratio to Full Sample
Tam Tien	256	93%	213	83.2%
Son Tra	255	86%	227	89.0%
Vinh Quang	248	96%	201	81.0%
Do Son	255	86%	222	87.1%
Total	**1,014**	**89%**	**863**	**85.1%**

Table 10. Reasons for rejecting choice scenarios (n = 1,014)

Reasons	Frequency	
The government is responsible for paying for all the costs of the improvements	43	52%
I don’t know which option is best, so I stick with the current situation	20	24%
We could have already afforded paying for better early warning service if we did not have corruptions and waste in the government	9	11%
I don’t agree with paying the fee through electricity bill	7	9%
I don’t really believe that the collected money will be spent on making the storm early warning service better	2	2%
I don’t believe that the program will achieve the improved objectives as described	1	1%

Table 11 presents a summary of the sociodemographic characteristics of the three datasets: full sample, protest excluded dataset, and certainty dataset. The datasets have very similar characteristics. In addition, Table 11 compares the characteristics of the sample respondents to the Vietnamese population using the 2009 Vietnam Population and Housing Census and Vietnam Household Living Standards Survey (VHLSS) 2010. The sociodemographic characteristic that differed in any appreciable way from that of the general Vietnamese population was the percentage of males. The 2009 Vietnam population census estimate was 49.4%, whereas the corresponding value in this research's sample was 83.6%. This may be due to the fact that storm preparedness (i.e., strengthening house) is normally a men's job. Besides, the surveys targeted coastal areas where fishing is a common occupation, and fishing is also traditionally a male occupation. Men pay more attention to the storm warning service, so they are more likely to be the representative of a household in responding to the storm-related interview. Another reason is that in Vietnamese households, especially in rural areas, men are usually the head of the household; therefore, men often represent their household in answering such government questionnaires. A high percentage of male respondents may be a good indication that the households in the sample seriously took part in the surveys, since the households chose the most relevant member to be a representative in responding to the interview. Besides, with the insignificance of "male" variable in the below section of conditional logit model results, it was expected that the high percentage of male respondents would not introduce some biases into the WTP estimates.

Table 11 also shows that the average age of respondents was higher than that of the Vietnamese population. A reason may be that older people who had more experiences of storms were more likely willing to participate in the interview. The monthly household income collected from the surveys was lower than that presented in VHLSS 2010. The reason may be because the survey sites are in coastal areas, and the poverty density in coastal areas of Vietnam is high (PEP 2008).

Table 11. Socioeconomic characteristics, by data sets and Vietnamese population

Socioeconomic Characteristics	Vietnamese Population	Full Sample	Protest Excluded	Certainty Sample
Age (> = 18 years)	39.6	47.5	47.5	47.2
Male (% male)	49.4%	83.6%	83.2%	84.5%
Income (in million VND per month per household)	5.4	4.4	4.5	4.6
Household size (# persons in household)	3.89	4.22	4.3	4.29
Education (% with more than high school)	30.0%	32.3%	32.6%	33.5%
N		1,014	932	863

3.2 Conditional Logit Models

The standard logit model, named conditional logit (CL) model, is a good starting point for the analysis of a discrete choice study. The CL model can be used to explore the data and behavior under concern in order to identify a possible specification for other more complicated and time-consuming models (Hensher, Rose, and Greene 2005). The analysis of this survey, therefore, started with the use of a CL model.

NLOGIT 4.0 was used to run the CL models: (1) including only the attribute variables, and (2) including the attribute variables and all relevant non-attribute variables (i.e., income, location). The two models were estimated for four datasets: full sample, protest excluded dataset, certainty dataset, and certainty dataset with protest excluded. The definitions of the variables are presented in Table 12. The results of the CL models are shown in Table 13 and Table 14.

Table 12. Definitions of variables

Variables	Descriptions
Attribute Variables	
ASC	Alternative specific constant (0 for the status quo [current situation], 1 for the improvement alternatives)
Accuracy Level 2	Accuracy of forecast information with Improvement Level 2 (1 if Improvement Level 2, otherwise 0)
Accuracy Level 3	Accuracy of forecast information with Improvement Level 3 (1 if Improvement Level 3, otherwise 0)
Update	Number of updates per day (8, 12, 16 times)
Mobile SMS	Mobile phone short message warning (1 if available, otherwise –1)
Cost	An one-off increase in the electricity bill (VND 0, 50, 150, 250 thousand)
Non-Attribute Variables	
Age	Age of respondents (in years)
Male	1 if respondents are male
Education	Education level of respondents in cardinal forms: 1 = Below primary school; 2 = Completed primary school; 3 = Completed secondary school; 4 = Completed high school; 5 = College/undergraduate degrees; 6 = Graduate degrees
Income	Monthly income of the household in cardinal forms: 1 = VND 0.9 million; 2 = VND 1.5 million; 3 = VND 3 million; 4 = VND 5 million; 5 = VND 7 million; 6 = VND 9 million ; 7 = VND 11 million; 8 = VND 13 million; 9 = VND 15 million; 10 = VND 17 million; 11 = VND 19 million; 12 = VND 21 million
Fishermen	1 if respondents are fishermen; otherwise 0
Central region	1 if respondents are living in Central region; otherwise 0
Household size	Size of the household
Elder above 70 years	1 if the households have elders who are above 70 years old; otherwise 0
Using mobile	1 if respondents are using mobile phone; otherwise 0
No. of information sources	Number of information channels that the respondents can use to access storm information
EWS perception	Respondents' attitude about the current early warning service; the larger satisfaction and reliance on the current service is, the higher score given
Attitude toward risk	Respondents' attitude toward storm risk; higher scores indicate that the respondents are more risk averse

Table 13. Results of CL models without covariates

Variables	Full Sample	Protest Excluded	Certainty Sample	Certainty Sample and Protest Excluded
ASC	0.49277*** (0.09216)	0.78153*** (0.09661)	0.14328 (0.09237)	0.37569*** (0.09557)
Accuracy Level 2	0.30265*** (0.07698)	0.30184*** (0.08048)	0.30929*** (0.07712)	0.30838*** (0.07977)
Accuracy Level 3	0.90703*** (0.08239)	1.03584*** (0.08830)	0.83194*** (0.08095)	0.92677*** (0.08537)
Update	0.05994*** (0.00996)	0.05991*** (0.01039)	0.05251*** (0.00994)	0.05185*** (0.01027)
Mobile SMS	0.34588*** (0.03167)	0.36226*** (0.03313)	0.35123*** (0.03161)	0.36369*** (0.03270)
Cost	–0.01498*** (0.00045)	–0.01621*** (0.00048)	–0.01339*** (0.00044)	–0.01425*** (0.00046)
Log-likelihood	–3,172.29500	–2,884.17300	–3,194.65400	–2,952.82400
Pseudo-R^2	0.24776	0.25590	0.24245	0.23819

Notes: (1) Standard errors are in parentheses. (2) *** refers to values that are significant at 1% level.

Table 14. Results of CL models with covariates

Variables	Full Sample	Protest **Excluded**	Certainty Sample	Certainty Sample and Protest Excluded
ASC	–1.95377*** (0.48284)	–0.77089 (0.50744)	–2.48178*** (0.48388)	–1.47655*** (0.50287)
Accuracy Level 2	0.31835*** (0.07993)	0.31719*** (0.08304)	0.32221*** (0.08045)	0.32048*** (0.08274)
Accuracy Level 3	0.97786*** (0.08561)	1.09607*** (0.09114)	0.90642*** (0.08447)	0.99167*** (0.08852)
Update	0.05846*** (0.01032)	0.05898*** (0.01070)	0.05112*** (0.01035)	0.05100*** (0.01063)
Mobile SMS	0.36313*** (0.03295)	0.37214*** (0.03424)	0.36854*** (0.03302)	0.37482*** (0.03397)
Cost	–0.01586*** (0.00047)	–0.01694*** (0.00050)	–0.01430*** (0.00047)	–0.01504*** (0.00048)
Interaction between ASC and Covariates				
Age	–0.00728** (0.00351)	–0.00864** (0.00367)	–0.01030*** (0.00351)	–0.01144*** (0.00363)
Male	0.01237 (0.09206)	0.10672 (0.09567)	0.03531 (0.09231)	0.11716 (0.09502)
Education	0.01549 (0.04642)	0.00186 (0.04836)	0.01158 (0.04650)	0.00037 (0.04798)
Income	0.10683*** (0.02118)	0.08932*** (0.02191)	0.14177*** (0.02104)	0.12794*** (0.02156)
Fishermen	0.11435 (0.09294)	0.12467 (0.09740)	0.17720* (0.09270)	0.18417* (0.09614)
Central region	0.55016*** (0.07491)	0.46666*** (0.07802)	0.56480*** (0.07483)	0.49128*** (0.07717)
Household size	0.04717** (0.02250)	0.02044 (0.02338)	0.06110*** (0.02244)	0.03694 (0.02310)
Elders above 70 years	0.12599 (0.08510)	0.15150* (0.08835)	0.07988 (0.08501)	0.10352 (0.08738)
Using mobile	0.19947** (0.09115)	0.23392** (0.09508)	0.21701** (0.09189)	0.24502*** (0.09485)
No. of info sources	0.06807** (0.02889)	0.06889** (0.03037)	0.02831 (0.02880)	0.02489 (0.02996)
EWS perception	0.08508*** (0.02946)	0.01543 (0.03146)	0.10683*** (0.02947)	0.04708 (0.03109)
Attitude toward risk	0.04948*** (0.01721)	0.05039*** (0.01813)	0.05817*** (0.01723)	0.05934*** (0.01795)
Log-likelihood values	–2,969.55500	–2,729.80200	–2,968.37200	–2,772.61100
Pseudo-R^2	0.27436	0.27791	0.27465	0.26659

Notes: (1) Standard errors are in parentheses. (2) ***, **, * refer to values that are significant at 1%, 5%, 10% levels, respectively.

Table 13 shows that all attribute variables have the expected signs. The respondents preferred more accurate storm information, and the positive coefficients of accuracy attributes increased as the improvement levels increased. They also wanted to have more updated storm information and mobile phone short message warning. The negative cost coefficient means that all the improvements should be provided at a cheaper cost. Most of the attribute variables were also statistically significant, with only one exception, the ASC in the certainty sample. In this research, ASC represents two types of utility: (1) the utility of moving away from the status quo and (2) the utility of Accuracy Level 1. In the certainty sample, all uncertain "yes" responses were recoded into a "no," which means that these uncertain respondents are interpreted as preferring to keep the current early warning service, and their utility of moving away from the status quo was zero.

The reduction in the utility of moving away from the status quo significantly decreased ASC in the certainty dataset. In Table 13, there are increases in the coefficients of Accuracy Level 3 and mobile SMS service when the protest respondents were removed. It seemed that the supporters of the improvement paid more attention to Accuracy Level 3 and the mobile SMS service. The results of the CL models with covariates also had significant attribute variables, except for the ASC in the protest excluded dataset (Table 14). The results also showed that the older respondents supported the improvement of a storm warning service less frequently compared to the younger respondents since they seem to have experiences and knowledge of storms. Hence, they can have their own forecast method and not rely on the early warning service. Another reason may be that the older respondents had lesser benefits from the future use of the improved warning service than the younger respondents.

The results of the CL models indicated significant differences between the WTP of the respondents living in the Central region and those living in the Northern region. Assuming that all other differences between samples from the Central region and Northern region were captured by the relevant variables (age, male, fishermen, etc.), the Central region variable will represent the location of the respondents.
The respondents living in the Central region, where storms are more frequent, had a larger support for the improvement of a storm warning service. In Table 14, the significant variable of income indicated that the respondents in households with higher income were more willing to pay for the improved warning service. With the significance of variable of using mobile, the respondents using mobile phone chose the improved programs more frequently.

The significance of the variable of attitude toward risk showed that the more risk averse the respondents were, the more frequently the respondents supported the improvements. The respondents' attitude toward risk should be investigated, since the value of the meteorological service (i.e., storm warning service) is an expected value that depends on respondents' subjective probabilities, which in turn are related to the individual's attitude toward risk. Risk attitude, however, seems sensitive to domains or situations. Literature on the psychology of decision making shows that people's attitude toward risk to achieve a gain is different from their attitude to avoid a loss (Levin et al. 2007; Plous 1993). Most people are risk averse to achieve a gain, but they become risk-seeking when it comes to losses. Another example is that managers appear to have different risk attitudes when making decisions involving personal versus company money or when evaluating financial versus recreational risks (Weber, Blais, and Betz 2002). To measure the respondents' risk attitude related to storm risk, this research applied four questions that specifically asked the respondents' opinions and behavior in storm preparedness (Table 15).

Table 15. Questions for measuring respondents' attitude toward storm risk

Question	Scoring
ATT1. In general, how would your best friend describe you as a risk taker?	1 = A real gambler 2 = Willing to take risks after completing adequate research 3 = Cautious 4 = A real risk avoider
To what extend you agree/disagree with the following statement:	
ATT2. A situation of evacuation but no storm landfall is better than a situation of no evacuation and damaged by storm	5 = Strongly agree 4 = Agree 3 = Neutral 2 = Disagree 1 = Strongly disagree
ATT3. If a friend or family member asked me about an approaching storm, I could not tell him or her what to expect.	1 = Strongly agree 2 = Agree 3 = Neutral 4 = Disagree 5 = Strongly disagree
Please indicate your likelihood of engaging in the following activity:	
ATT4. You always seek out more up-to-date information of an approaching storm than what is provided on the television or radio.	5 = Very high 4 = High 3 = Medium 2 = Low 1 = Very low

Table 14 also shows some differences between the data sets. The variable of fishermen was only statistically significant in the models with the certainty data set. It implies that respondents who were fishermen were more certain about their support for the improvements in the early warning service for storm. This is reasonable since fishermen will be the main beneficiary of the improvements.
The insignificance of the variable of household size and the higher average value of household size in the protest-excluded dataset indicated that the smaller households were more likely to be a zero-protest bid and were then removed from the protest-excluded data set. The conclusion can be that smaller households support less frequently the improvements. It is easier for the small household to make a decision on storm preparedness (i.e., evacuation), such that they may not require additional and better storm information provided by the early warning service.

The variable of EWS (early warning services) perception is similar to the household size variable in terms of statistical significance. The EWS perception variable was measured by two questions presented in Table 16, and the correlation coefficient of the two questions was 0.45. The variable of EWS perception had an average score in the protest-excluded dataset (8.04) higher than the equivalent score in the full sample (7.99). The zero-protest bids removed were likely the lower score, or another way of saying, the respondents who were less satisfied and confident of the current service rejected the improvement scenarios.
The respondents giving high score of EWS perception chose the improvement options more frequently.

In Table 14, the last variable that should be taken into account was the variable of number of information sources, which was statistically significant in the full sample and in the protest-excluded sample, but not in the certainty sample. For the average number of channels, which the respondents used to access the early warning service, the certainty sample (3.6044) was slightly lower than the equivalent value in the full sample (3.6048). This result indicates that some respondents using a slightly above average number of information channels were uncertain about their "yes" response, and they were accordingly recoded as zero bids in the certainty data set. The recoding resulted in a significant decrease in the number of respondents with positive WTP and an above average number of channels to access storm information. These uncertain respondents may think that while the early warning service is freely accessed by several channels, the service should be a public good provided freely for everyone.

Table 16. Questions for measuring respondents' perception of current early warning service for storm

Question	Scoring
Q3. Please indicate your satisfaction with the current early warning service for storm. "Satisfaction" means fulfillment of your need or want by using the current service.	1 = Very dissatisfied 2 = Dissatisfied 3 = Neutral 4 = Satisfied 5 = Very satisfied
Q4. Please indicate your confidence in the current early warning service for storm. "Confidence" means that you are certain of the quality of the early warning service, and use the service to support your decision of storm preparedness	1 = Very low 2 = Low 3 = Medium 4 = High 5 = Very high

3.3 Mixed Logit Models

A mixed logit (ML) is a highly flexible model that can be used to solve three limitations of the standard conditional logit (Train 2009). First, a CL model cannot capture unobserved preference heterogeneity. Second, a standard logit model does not allow for a type of ''panel'' data, in which each respondent answers a series of choice questions. Lastly, a standard logit cannot relax the assumption of independence from irrelevant alternatives (IIA). In this study, ML models were estimated for all of the attribute variables except for the cost attribute, which were assumed as random parameters. Normal distribution is commonly applied for random parameters in an ML model (Greene 2008); thus, the ML models in this research also had normal distribution for the random parameters with 1,000 draws. The ML models here allowed free correlation among the random parameters. Table 17 shows the results of ML models without covariates.

Table 17. Results of ML models without covariates

Variables	Full Sample		Certainty Sample	
	Mean	SD	Mean	SD
ASC	1.15028*** (0.18688)	2.28773*** (0.27671)	0.57957** (0.22596)	2.72966*** (0.32199)
Accuracy Level 2	0.55617*** (0.17463)	1.06733*** (0.18090)	0.59704*** (0.20691)	1.13976*** (0.23516)
Accuracy Level 3	1.67544*** (0.19307)	1.68307*** (0.37778)	1.61640*** (0.22316)	1.81367*** (0.42554)
Update	0.08069*** (0.02425)	0.07276** (0.03179)	0.08082*** (0.02801)	0.08525** (0.03686)
Mobile SMS	0.57262*** (0.07815)	1.17979*** (0.11412)	0.64288*** (0.09326)	1.25184*** (0.11122)
Cost	–0.02795*** (0.00121)		–0.02794*** (0.00129)	
Log-likelihood values	–2,846.452		–2,750.147	
Pseudo-R^2	0.32502		0.34786	
Variables	Protest Excluded		Certainty Sample and Protest Excluded	
	Mean	SD	Mean	SD
ASC	1.51957*** (0.17727)	2.09310*** (0.27189)	0.91460*** (0.20965)	2.45125*** (0.30361)
Accuracy Level 2	0.56682*** (0.17339)	1.19045*** (0.19731)	0.58346*** (0.19016)	1.06767*** (0.19914)
Accuracy Level 3	1.81164*** (0.19179)	1.74847*** (0.21727)	1.71399*** (0.20882)	1.66553*** (0.38401)
Update	0.07989*** (0.02327)	0.06904 (0.05681)	0.08054*** (0.02631)	0.07371* (0.03817)
Mobile SMS	0.56998*** (0.07742)	1.18026* (0.70071)	0.63571*** (0.08513)	1.20136*** (0.13296)
Cost	–0.02817*** (0.00121)		–0.02740*** (0.00127)	
Log-likelihood values	–2,664.836		–2,614.218	
Pseudo-R^2	0.31249		0.32555	

Notes: (1) Standard errors are in parentheses. (2) ***, **, * refer to values that are significant at 1%, 5%, 10% levels, respectively.

All attributes and their standard deviations were significant in the ML models, except for the standard deviation for ''Update" attribute in the sample with protest excluded. All the mean coefficients had the expected signs. The respondents preferred more accurate and more updated storm information with the mobile phone short message warning, but all the improvements should be provided at a cheaper cost.
The significance of the estimated standard deviations implies that there was heterogeneity in the preferences for these attributes. Furthermore, the relative magnitude of the standard deviations implies that there was the probability that people had the reverse (negative) preference for the attributes.
The probability of a negative sign indicates that some respondents did not prefer an improvement on a particular attribute, and they were satisfied with the current level of the attribute. There was also a correlation in the heterogeneity of preferences between attributes. From the correlation matrix in Table 18, there was a strong positive correlation between a preference for high level of "Accuracy" and the other attributes of "Update" and "Mobile SMS."

Table 18. Correlation matrix for random parameters in ML model with full sample

Attribute	ASC	Accuracy Level 2	Accuracy Level 3	Update	Mobile SMS
ASC	1.00000				
Accuracy Level 2	–0.44205	1.00000			
Accuracy Level 3	–0.13485	0.82133	1.00000		
Update	–0.13061	0.94567	0.86145	1.00000	
Mobile SMS	–0.58725	0.57665	0.72436	0.43663	1.00000

Note: Results of the correlation matrix in ML models with the other three samples are similar

To determine whether the ML models were superior to the CL models, log likelihood ratio tests were conducted. Table 19 shows that the test statistic values were larger than the critical values, so the null hypothesis (i.e., ML models are no better than CL models) was rejected. Without covariates, the ML models should be used to capture the heterogeneous preferences.

The ML models were used to estimate the WTP for a change in the attributes and the total WTP for improvement programs in the early warning service for storm in Vietnam. The total WTP estimates for the two improvement programs were as follows:

+ **Medium improvement**: accuracy improvement Level 2, update frequency of 12 times and mobile phone short message warning.

+ **Maximum improvement:** accuracy improvement Level 3, update frequency of 16 times and mobile phone short message warning.

Table 20 shows that in most of the models, the WTP for Accuracy Level 3 was higher than that of Accuracy Level 2 and mobile phone short message warning. The improvement in Accuracy Level 3, therefore, was more preferred than the other options of improvement in Accuracy Level 2 and availability of mobile phone short message warning. The higher WTPs for the Mobile SMS in the certainty data sets indicate that the respondents who were certain about their choices paid more attention to the availability of mobile phone short message warning. In this research, frequency of update seemed to receive the least attention relative to the accuracy and mobile SMS attributes, since the maximum WTP for improving the update attribute was about VND 32,000 for the highest level of 16 times per day. The investments in EWS for storm should be paid for the improvements in accuracy and mobile SMS attribute.

Table 19. Results of the log likelihood ratio tests

Models without Covariates		Full Sample	Protest Excluded	Certainty Sample	Certainty Sample and Protest Excluded
Log-likelihood values	CL Model	−3,172.295	−2,884.173	−3,194.654	−2,952.824
	ML Model	−2,846.452	−2,664.836	−2,750.147	−2,614.218
Statistic Value		651.686	438.674	889.014	677.212
0.5% critical value of χ^2 at 15 degrees of freedom		24.996	24.996	24.996	24.996

Table 20. Mean estimates of WTP for a change in the attributes by ML models (in ‘000 VND)

Attribute	Full Sample	Protest Excluded	Certainty Sample	Certainty Sample and Protest Excluded
Accuracy Level 1	41.1528*** (7.1145)	53.9340*** (6.5757)	20.7440** (8.2431)	33.3825*** (7.8648)
Accuracy Level 2	61.0505*** (6.1866)	74.0522*** (5.4848)	42.1131*** (6.8138)	54.6784*** (6.4456)
Accuracy Level 3	101.0940*** (6.9777)	118.2350*** (6.4818)	78.5980*** (7.8814)	95.9423*** (7.5337)
Frequency of update	2.88677*** (0.8518)	2.8355*** (0.7969)	2.89266*** (0.9822)	2.9396*** (0.9329)
Mobile phone short message warning	40.9726*** (5.1160)	40.4606*** (4.8588)	46.0201*** (5.8108)	46.4061*** (5.4402)

Notes: (1) Standard errors (based on the Krinksy–Robb simulation using 1,000 draws) are in parentheses. (2) *** refers to values that are significant at 1% level.

In Table 21, the total WTP for a medium-improvement program that was estimated from the full sample was about VND 114,000 (~USD 5.5).[2] The total WTP in this research was a one-off payment, and the respondents were informed that the payment would be used for implementing the Strategy for Development of Hydro-meteorological Service, which is operational until 2020. So assuming that this payment would be used for investments in the meteorological systems in 10 years, the first year payment in 2010 of a Vietnamese household would be about 0.024% of the income of VND 52.8 million.[3] Lazo et al. (2010) estimated the WTP for an improved hurricane forecasting in the US; the results showed that the WTP for the intermediate program is about USD 14.34 per household per year. The WTP of US households accounts for 0.029% of the annual income of USD 50,221.[4] It appears that the results in this research were similar to the available results in literature.

Table 21. Total WTP estimates by ML models (in '000 VND)

Program	Full Sample	Protest Excluded	Certainty Sample	Certainty Sample and Protest Excluded
Medium improvement	113.5700*** (5.6990)	125.8550*** (5.6190)	99.7038*** (6.7196)	112.8430*** (6.2005)
Maximum improvement	165.1610*** (6.9513)	181.3790*** (6.4459)	147.7590*** (8.0823)	165.8650*** (7.3439)

Notes: (1) Standard errors (based on the Krinksy–Robb simulation using 1,000 draws) are in parentheses. (2) *** refers to values that are significance at 1% level.

3.4 Latent Class Models

The results of the ML models showed the existence of heterogeneous preferences for improvements in the storm warning service in Vietnam. By allowing model parameters to vary randomly over individuals, the ML models incorporated and accounted for heterogeneity. However, the ML models are not well-suited to explain the sources of heterogeneity (Boxall and Adamowicz 2002). In the ML models, the results may show heterogeneous preference across individuals, but in reality, especially for a case of public goods, it is difficult to design and produce goods suitable for each individual. Therefore, latent class models (LCM) was also applied to the datasets to understand the sources of heterogeneity.

The underlying theory of LCM posits that individual behavior depends on observable attributes and on latent heterogeneity that varies with factors that are unobserved by the analyst. Thus, it is assumed that individuals are implicitly sorted into a set of latent classes, but which class contains any particular individual, whether known or not to that individual, is unknown to the analyst (Greene and Hensher 2003).
If heterogeneity is found across the classes—which could be identified both by demographic variables and by characteristics of respondents—then the sources of heterogeneity can be explained by the differences in the classes. Furthermore, LCM obviates the other two limitations of a standard logit by allowing for the type of ''panel'' data and by relaxing the IIA assumption.

Using the attributes (including cost) as preference parameters and explaining class membership by a constant, along with demographic and attitudinal variables including age, education, income, central/northern location, fisherman, household size, and attitude toward storm risk, the three-class model best represented the data, according to the usual statistical information criteria (Boxall and Adamowicz 2002; Burton and Rigby 2009). The results from the three-class models are presented in Table 22 and Table 23. Table 24 and 25 present WTP for attributes and total WTP estimated from the LCM models.

[2] USD 1 = VND 20,800 (from website of State Bank of Vietnam, accessed on 21/11/2011)

[3] The 10-year income is estimated based on the full sample mean of income.

[4] US Census Bureau (http://quickfacts.census.gov/qfd/states/00000.html, accessed on 21/11/2011)

Table 22. Results of LCM model estimated for full sample

Variables	Mean Coefficients		
	Class 1	Class 2	Class 3
ASC	5.40556*** (0.91923)	0.40219*** (0.10682)	−2.42863*** (0.32410)
Accuracy Level 2	−0.98971* (0.55452)	0.77954*** (0.09122)	1.66945*** (0.25695)
Accuracy Level 3	0.05244 (0.57336)	1.49478*** (0.10020)	2.43802*** (0.22959)
Update	0.30082*** (0.09149)	0.07542*** (0.01221)	0.10911*** (0.02946)
Mobile SMS	0.66954*** (0.24951)	0.62477*** (0.03446)	0.33577*** (0.09459)
Cost	−0.06683*** (0.00693)	−0.01100*** (0.00049)	−0.01949*** (0.00143)
Covariates Explaining Latent Class Membership			
Constant	−3.27908*** (0.96650)	−3.81061*** (1.02194)	
Age	0.01579* (0.00950)	−0.01948** (0.00989)	
Education	0.28426** (0.12763)	0.16322 (0.13517)	
Income	0.00010*** (0.00004)	0.00017*** (0.00004)	
Fishermen	0.03254 (0.22223)	0.40598* (0.22158)	
Central region	0.68654*** (0.19430)	1.13341*** (0.20837)	
Household size	−0.04131 (0.06057)	0.10363* (0.06299)	
Attitude toward risk	0.09768** (0.04645)	0.18263*** (0.04988)	
Log-likelihood values	−2,669.443		
Pseudo-R^2	0.36700		

Notes: (1) Group 3 is the baseline. (2) Standard errors are in parentheses. (3) ***, **, * refer to values that are significance at 1%, 5%, 10% levels, respectively.

Table 23. Results of LCM model estimated for certainty sample

Variables	Mean Coefficients		
	Class 1	Class 2	Class 3
ASC	15.2588 (106231.0000)	0.41461*** (0.09933)	−3.80426*** (0.52918)
Accuracy Level 2	26.9101 (212462.0000)	0.67486*** (0.08639)	−0.06082 (0.34252)
Accuracy Level 3	28.5555 (212462.0000)	1.48451*** (0.09773)	1.10126*** (0.30516)
Update	0.5545** (0.2199)	0.08369*** (0.01170)	0.05558 (0.04555)
Mobile SMS	0.3643* (0.1958)	0.57729*** (0.03238)	1.35661*** (0.19729)
Cost	−0.3330 (2124.6000)	−0.01142*** (0.00046)	−0.01884*** (0.00228)

Table 23 continued

Variables	Mean Coefficients		
	Class 1	Class 2	Class 3
Covariates Explaining Latent Class Membership			
Constant	−2.32441*** (0.81027)	−2.53644*** (0.80716)	
Age	0.01172 (0.00874)	−0.02618*** (0.00874)	
Income	0.00012*** (0.00003)	0.00017*** (0.00003)	
Central region	0.23717 (0.18035)	0.83250*** (0.18302)	
Household size	−0.00663 (0.05710)	0.11905** (0.05626)	
Attitude toward risk	0.08762** (0.04440)	0.15928*** (0.04517)	
Log-likelihood values	−2,582.662		
Pseudo-R^2	0.38757		

Notes: (1) Group 3 is the baseline. (2) Standard errors are in parentheses. (3) ***, **, * refer to values that are significant at 1%, 5%, 10% levels, respectively.

Table 24. WTP for a change in the attributes by LCM models

Attribute	Full Sample			Certainty Sample		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Accuracy Level 1	80.888***	36.548***	−124.621***	45.826	36.315***	−201.901***
Accuracy Level 2	66.078***	107.386***	−38.956***	126.645	95.426***	−205.129***
Accuracy Level 3	81.673***	172.380***	0.482	131.587	166.343***	−143.454***
Freq of update	4.501***	6.853***	5.599***	1.665	7.330***	2.950
Mobile phone short message warning	20.038***	113.548***	34.460***	2.188	101.129***	143.997***
Attribute	**Protest Excluded**			**Certainty Sample and Protest Excluded**		
	Class 1	**Class 2**	**Class 3**	**Class 1**	**Class 2**	**Class 3**
Accuracy Level 1	71.8449***	40.5341***	−129.241***	38.520***	38.543***	−189.624***
Accuracy Level 2	58.6887***	107.199***	15.100	84.574***	97.823***	−201.987***
Accuracy Level 3	74.9515***	169.646***	76.380***	97.538***	167.383***	−112.948***
Freq of update	4.81991***	6.740***	2.497	4.724**	7.271***	2.267
Mobile phone short message warning	24.4705***	118.508***	1.741	5.805	100.782***	149.415***

Note: ***, ** refer to values that are significant at 1%, 5% levels, respectively.

Table 25. Total WTP by LCM models

Program	Full Sample			Certainty Sample		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Medium improvement	104.122***	248.347***	17.898*	135.493	225.876***	−49.333**
Maximum improvement	137.722***	313.341***	57.335***	147.095	296.793***	12.341
Medium improvement	102.439***	252.665***	26.828**	109.277***	227.691***	−43.504*
Program	**Protest Excluded**			**Certainty Sample and Protest Excluded**		
	Class 1	**Class 2**	**Class 3**	**Class 1**	**Class 2**	**Class 3**
Maximum improvement	137.981***	315.112***	88.108***	141.138***	297.251***	45.535***

Note: ***, **, * refer to values that are significant at 1%, 5%, 10% levels, respectively.

The results of total WTP in Table 25 showed that the respondents in Class 2 exhibited the maximum support for the improvements in all attributes of an early warning service for storm. These strong supporters had the highest total WTP of VND 315,000 (~USD 21) which was higher than the highest cost level of VND 250,000 (~USD 12). The significance of negative "age" and positive "income" variables showed that the respondents in Class 2 were younger and had higher income; they were exposed to higher storm risk (living in Central region with significant and positive "Central region" variable, working as fishermen with significant and positive "fisher" variable). Furthermore, they had to take care of a big family (since the "household size" variable was significant and positive), and they were also more risk averse (since the "attitude toward risk" variable was significant and positive). Therefore, it was reasonable for the respondents in Class 2 to be the strong supporters of the improvements.

The respondents in Class 3 showed minimum support for the improvements in the storm warning service. Since the utility of moving away from the status quo (ASC) was confounded with the utility of accuracy improvement, the negative coefficients of accuracy attributes showed that the respondents in Class 3 were more likely to choose the status quo option. The respondents here had relative low income (since the "income" coefficients were positive in both Class 1 and Class 2) and were living in the Northern region (because the "Central region" variable had positive coefficients in both Class 1 and Class 2). They were also risk lovers (since the "attitude toward risk" coefficients were positive in both Class 1 and Class 2). These characteristics of the respondents explain their minimum total WTP. With the relatively large and positive coefficients of "mobile SMS" attribute, the respondents in Class 3 can be identified as the supporters of the mobile phone short message warning. They were less risk averse, so they were more willing to try the new mobile SMS service.

Finally, the respondents in Class 1 exhibited medium support for the improvements. However, respondents in Class 1 had relatively low WTP for the new mobile SMS service. They may be the traditional users of the storm warning service. A reason may be they were older than the respondents in the other classes (since the coefficient of "age" variable had positive sign).

4.0 CONCLUSIONS AND POLICY IMPLICATIONS

Vietnam is one of the most storm-prone countries in the Mekong Region. In recent years, intense storms have hit Vietnam more frequently and the fatalities caused by storms have increased. This evidence shows that the severity of storm risk in Vietnam has increased. Recognizing the increased severity of storms, the Government of Vietnam plans to improve the country's storm warning service. Improving storm early warning service will be one of the key measures to help Vietnamese people, especially the poor, to adapt to the more severe environmental risks. If all improvement programs in storm forecasting and warning services were to be implemented, then the Government of Vietnam would have to source additional financial investment, such as international funding for adaptation to climate change. Information on the benefits of improved warning services for storms will be helpful in the cost-benefit analysis of these programs, which in turn will assist international negotiations for adaptation funding.

After removing hypothetical bias, the total "certain" WTP for the medium improvement program was estimated at about VND 100,000–110,000 (~USD 4.8–5.3)[5] per household. According to the 2009 Vietnam Population and Housing Census, Vietnam has 22,444,322 households. The total WTP by Vietnamese people, therefore, was estimated at approximately VND 2,350 billion. On 25 June, 2010, the Prime Minister of Vietnam approved the program "Modernize Forecasting Technologies and Monitoring Systems for Hydro-Meteorological Services in 2010–2012" with a total cost of VND 1,391 billion. The total WTP for the medium options will cover the total cost of this program.

The maximum benefit estimated for the certainty sample that can be considered as "true" benefit was about VND 148,000–168,000 (~USD 7.1–8.1) per household. The maximum benefit of improving early warning service for storm in Vietnam was estimated at about VND 3,322–3,771 billion (~USD 160–181 million). This information will be useful for international donors when they consider investing in adaptation measures for climate change in the developing countries like Vietnam.

[5] USD 1 = VND 20,800 VND (from website of State Bank of Vietnam, accessed on 21/11/2011)

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