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FRESHWATER CONSERVATION, DRINKING WATER QUALITY AND CLIMATE CHANGE ADAPTATION: A CASE STUDY ON NEPAL

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A Dissertation Presented

by

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DEDICATION

To my parents, Moti Bahadur Kunwar and Sharada Kunwar, who have always been there with me, supported me in every step and have pushed me throughout my life. And, to my two sisters, Sofiya and Supriya Kunwar.

This is for all of us.

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Freshwater Conservation, Drinking Water Quality & Climate Change Adaptations: A Case Study on Nepal

by

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ABSTRACT

Our world today faces a myriad of unprecedented environmental challenges that transcends spatial and temporal reach. These problems involve interconnected ecological and social systems operating on multiple scales and include issues like climate disruption, water stress, food security, biodiversity loss, over-population and species declines and extinctions. These issues are more acute in rapidly growing nations like Nepal, where environmental protection is often considered a luxury. Such environmentally unsound development practices will not only create an imbalance in the ecological and the social functioning and dynamics, but it also threatens the future development of the country itself. In this dissertation, I investigate three major environmental challenges in Nepal: problems with freshwater conservation, issues with drinking water quality and availability, and concerns with climate change adaptation and mitigation.

To approach these environmental challenges, chapter 2 employs a choice experiment method to assess the potential for a sustainable management of the Danda River system in Nepal. Using a Generalized Multinomial Logit model (GMNL) to account for households' preference and scale heterogeneity, I find that respondents are willing to pay (WTP) about $17.06/year to improve the quality of the river water, and $13.46/year to introduce vegetation in the Danda riverbank. The results also suggest a presence of local spatial heterogeneity in the preference for the river ecosystem services. Households located in the central region in the urban town of Siddharthangar preferred the river ecosystem services to households located anywhere else. Further, I also find evidence for preference of local governance, with the households' favoring a community-based management of the Danda river system. This finding highlights the need for policymakers to decentralize the management of local resources to communities to enhance interest in conservation of common pool resource like the Danda river system.

In my third chapter, I investigate water averting behavior by placing a particular emphasis on the divergence between a household's perception of their water quality and the objective water quality level. The findings indicate that the gap between perception and reality indeed plays a role in a household's decision to adopt water treatment measures. Households with minimal divergence between subjective and objective water quality were more likely to engage in water averting behaviors than households otherwise. In my fourth chapter, I employ a hedonic model to investigate the impact of climate change on agricultural productivity in Nepal. Findings suggest that while the Nepalese farmlands are sensitive to increases in temperature and precipitation, the effects vary depending on whether the farmlands were irrigated or not.

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Chapter 1: Introduction

1.1 Environmental Challenges of the 21st century

The environment has now become a major constraint on human progress, thus, sustainable management of the environment and natural resources is vital for the economic growth and human wellbeing. An efficient management of the renewable and non-renewable natural resources provides ample natural capital that can serve as the foundation for continued inclusive growth, food security and poverty alleviation. The integrity and functionality of these vital natural assets, however, are increasingly being compromised by human actions. The major global environmental challenges in today's era are emerging from interconnected ecological and social systems operating on multiple scales and include global warming, climate change, freshwater crisis, toxic waste, water and air pollution, acid rain, biodiversity loss, deforestation, invasive species and public health issues.

It is now widely recognized that some damage to the environment is difficult, if not impossible, to reverse. In fact, there is a growing evidence which suggests that the important tipping points, leading to irreversible changes in major ecosystems and the planetary climate system, may already have been reached or passed (IPCC, 2014). About 60 to 70% of the world's ecosystems are degrading faster than they can recover (MEC, 2005). Ecosystems as diverse as the Amazon rainforest and the Arctic tundra, for example, may be approaching thresholds of dramatic change through warming and drying. Mountain glaciers are in alarming retreat and the downstream effects of reduced water supply in the driest months can have repercussions that transcend generations (MEC, 2005).

Such mismanagement of the environment and natural resources not only creates an imbalance in the functioning and dynamics of the natural ecosystem, but it also results in significant economic losses which leads to a vicious cycle of further environmental degradation. For instance, about $80 billion are squandered each year to ocean fisheries mismanagement (Arnason and de Fontaubert, 2017). Air pollution is now the fourth leading risk factor for premature death, contributing to 1 in 10 of all deaths worldwide and resulting in significant losses of welfare and income. The global cost of air pollution due to lost labor income from death alone amounts to $225 billion annually (World Bank, 2016). Likewise, the global cost of climate change on annual consumption loss is $520 billion, and it is predicted that extreme weather events will push more than 100 million people to poverty by 2030 (Hallegatte et al., 2015; Hallegatte et al., 2016).

At the core of the major environmental challenges in today's world perhaps lies urbanization and overpopulation. Urbanization is a defining issue of our time with more rural landscapes being transformed to cities at an accelerating pace. According to the World Health Organization, close to 54% of the global population lives in the urban cities and urban growth rate is around 2% per year (WHO UN Habitat, 2017). Ecological responses to anthropogenic impacts stemming from urbanization and overpopulation are complex and interacting, occurring on all spatial and temporal scales. Urbanization is an important driver of climatological and ecological problems, and it alters both biotic and abiotic ecosystem properties within, surrounding, and even at great distances from the urban areas.

The impact of urbanization on the environment are likely to be more acute in the developing countries located in Asia, Africa and South America. Countless South and East Asian cities have already undergone unpreceded rural-to-urban population shifts as a result of chronic poverty, political conflicts, and the lure of opportunities created by globalization. This has led to devastating ecological disruption in the form of habitat loss, polluted waterways, and unbreathable air. The impact of these environmental degradations on human health and well-being has been highly detrimental. For example, India and China each lose more than 1 million people annually due to air pollution (State of Global Air, 2017). Likewise, scores of children throughout South Asian cities die of waterborne diseases due to unhealthy living and poor sanitation. Gunther and Fink (2016) assert that appropriate investment in sanitation and related infrastructure can reduce child deaths by 2.2 million annually. These environmental concerns have direct and indirect influence on the livelihood of people through various systems such as health, sanitation, infrastructure, settlements, tourism, agricultural productivity, and social networks.

A prime example of urbanization and its impact on the environment in the developing world is nowhere more apparent than in Nepal. Urbanization in Nepal has been the inevitable response to stagnating economic conditions in rural areas. Thapa & Murayama (2009) report that the urbanization process in the major cities in Nepal, which has increased by more than four times in the last four decades has caused a major fragmentation of the landscape and the ecology. These expansions have put significant dent on natural resources, eco-systems, and the environment (river, vegetation, and the wild life), and the impact is visibly evident in the cities. The cities in Nepal today face a host of environmental problems, from water shortages and air pollutions to large-scale deforestation, adverse climatic conditions and habitat degradation, affecting both human health and welfare. These environmental problems ultimately transcend spatial and temporal boundaries, and as such, the rural Nepalese communities are also deeply affected as they are more vulnerable cannot quickly adapt to the changing environment led by urban pressure.

The impact of environment degradation on ecosystem services and ultimately on the livelihood security are mostly case specific. An initial step toward providing an optimal mitigation strategy is to understand the intricate link between human activities and the environment. Through my dissertation, I seek to explore three major environmental challenges in Nepal: problems with freshwater ecosystem management and conservation, challenges with drinking water quality and availability, and issues related to climate change adaptation and mitigation. The first two environmental issues will be a case study of the environmental challenges on the urban sector in Nepal, while the third issue focuses the rural sector. Below, I provide a brief overview of the three environmental challenges.

1.1.1 Freshwater Ecosystem:

Freshwater biomes make up less than 2.5 percent of the total available volume of water on Earth, and less than 1 percent is available for human consumption and ecosystem (Gleick, 2000). Nonetheless, these resources are an essential element of life and our society is heavily dependent on the freshwater ecosystem. Freshwater systems provide an provide an array of ecological functions and services, ranging from biodiversity, water quality maintenance, water supply to households, industries and agriculture, and flood and flow controls, to recreational and aesthetic value.

Yet, we have not always been careful on using these resources in a sustainable manner. Freshwater ecosystem services are one of the most exploited ecosystems and are considered to have been degraded beyond levels that can be sustained at current demands (MEC, 2005). The anthropogenic impacts of freshwater are global and include alteration in flow, chemical runoff and pollution, species extinctions, species invasions, wastewater floods, thermal alterations, global climate change, and increases in ultraviolet radiation (Dodds et al., 2013). In fact, freshwater ecosystems tend to have the highest proportion of species threatened with extinction (MEC, 2005).

The human impacts on freshwater ecosystems are even more severe in the urban areas. Today, more than 50 percent of the world's population lives in and around the cities. With the ever-expanding urbanization pressure, the extreme usage and exploitation of the water system have also been growing to meet the rising demands for irrigation, farming, commercial usage, and residential needs. Water withdrawals from rivers and lakes for irrigation or for urban or industrial use has more than doubled between 1960 and 2000 (MEC, 2005). Globally, humans are already using slightly more than 10% of the total available renewable freshwater supply for household, agricultural, and industrial activities (MEC, 2005). The aftermath of urban reliance on freshwater systems have mostly been devastating. The waste generated in the urban areas from domestic and industrial waste, agricultural discharge to non-point source pollution all mostly end up in the river systems, which severely deteriorates the health of the freshwater ecosystems.

Whether for irrigation, recreation, or domestic needs, any interaction with a contaminated riverfront cannot be good news for human health. Likewise, unhealthy river fronts filled with garbage and chemical waste cannot support any plants or wildlife. So, the health and wellbeing of many of the urban areas and the human population must be understood as an interdependent system alongside the health and wellbeing of the surrounding riparian systems. In dealing with these issues, many cities in the developing world still lag far behind when it comes to studying the science of the problem, educating the public for awareness, or investing in infrastructure.

One prime example where urbanization has had an adverse impact on the freshwater systems is in Nepal. The most discernable case in point is the Bagmati River in the capital city of Nepal. Dotted by hundreds of age-old magnificent temples and shrines, the holy river of Bagmati has become a symbol of riparian disaster rather than a source of solace and spiritual inspiration. Years of neglect and complacent attitudes, combined with the lack of proper urban planning, resources, and the waste management strategies, have all contributed to the bleakness of this once pristine river system. A similar fate to Bagmati River is currently occurring in the Danda River system in the rapidly growing city of Siddharthangar, Nepal. One of the many threats of urban sprawl in Siddharthangar is the diffuse pollution dumped into the Danda River, where poor drainage systems carrying the road runoff from the surrounding residential and industrial zones are gradually worsening the river ecosystem.

An inevitable consequence of the deteriorating Danda river system has been the rapid loss of biodiversity and aquatic species. Furthermore, irrigation from these water sources are no longer possible, and people can no longer engage in water-based recreational activities they once enjoyed. The severity of this issue has had a rippling effect on the local economy, as various community segments, in particular the fishermen and the farming populations, have been forced to take up to new activities to sustain their livelihoods (IUCN, 2012). Moreover, an unhealthy Danda River could also deter the record influx of tourists that come to Lumbini via Siddharthangar every year (Nyaupane et al., 2014), placing a significant burden on the economy of the country itself. The intertwined nature of the Danda River with the communities that rely on it necessitates a thorough analysis to ensure the well-being of the health of the river and its surrounding riparian system. In my second chapter, I explore the value that people in Siddharthanagar place on a clean and healthy Danda River.

1.1.2 Drinking Water Quality & Availability

Access to safe drinking-water is a fundamental human right, yet, millions of people globally lack adequate access to drinking water in two arenas: quality and availability. Global figures indicate that as of 2015, only 71 percent (5.2 billion people) of the population have access to a safely managed drinking water service on their premises, while almost 900 million people do not have sufficient access to basic drinking water services

(WHO and UNICEF 2017). Over 250 million people globally still spend over 30 minutes per round trip to collect water from an improved source, while for more than 160 million people, surface water sources are the only source of drinking water (WHO and UNICEF 2017).

The consequence of a lack of access to clean water and sanitation can be devastating to the human health in particular. The World Health Organization (WHO) estimates that improving water, sanitation and hygiene could prevent at least 9.1 percent of the global burden of disease and 6.3 percent of all deaths (Pruss-Ostun, 2008). Diarrhea represents a significant share of this burden, resulting in an estimated 4 billion cases and 1.9 million deaths each year of children under 5 years, or 19 percent of all such deaths in developing countries (Boschi-Pinto, Velebit and Shibuya, 2008).

The widespread water quality concerns in the developing world are no exceptions to Nepal. The availability of water is not as much of a significant concern since more than 88% of the households had access to a water source in 2015 (WHO /UNICEF, 2017). However, improved access does not necessarily reduce the risk of microbiological contamination in the drinking water, thus, water quality remains an issue. In fact, only about 27% of the population has access to safely managed water supplies free from contamination (WHO /UNICEF, 2017). This issue has contributed to major health outbreaks in Nepal ranging from infant and child mortality rates to high incidences of fecal-orally transmitted diseases. Water quality concerns in the country are further exacerbated due to the rapid and haphazard urbanization that has resulted in high population density in the major urban areas.

One straightforward technique to prevent the occurrence of diarrhea and other waterborne diseases in countries like Nepal is through household water treatment and safe storage (HWTS) practices. While HWTS is not a new approach and households have historically employed variety of methods to improve the appearance and taste of their drinking water; it's recognition as a key strategy for improving public health is just emerging. An increasing number of studies show that HWTS such as boiling, filtration or chlorination water can significantly reduce diarrheal diseases (WHO, 2013). Nevertheless, implementing such HWTS practices require households to be pro-active and aware about their water quality levels so they can modify their water handling behavior. My third chapter explores the HWTS behavior of households in Siddharthanagar, Nepal by looking at the divergence between the perception and objective water quality level in affecting households' water averting behaviors.

1.1.3 Climate Change Adaptation and Mitigation

Climate change is emerging as a significant threat facing humanity in the 21st century. The fluctuating patterns of temperature, precipitation and the frequency of extreme weather events are disrupting the delicate balance of climate and life, with serious impacts on food and agriculture, water sources, and health. Agriculture, in particular, could be seriously impacted through climate change due to its dependence on natural weather patterns and climate cycles for its productivity. In fact, there is a general consensus among climate change researchers that changes in temperature and precipitation will lead to fluctuations in land and water regimes that will ultimately affect agricultural productivity (World Bank, 2003).

Many past studies have investigated the impact of climate change on agriculture and the evidence has so far indicated that the productivity of agricultural activities is highly sensitive to climate change. The sensitivity of climate change on agriculture can be more acute on developing nations because of their heavy reliance on rain-fed agriculture. Moreover, with the rising occurrence of extreme climatic events with droughts, floods and heatwaves becoming more common in the 21st century, the loss to agricultural nations that cannot adapt easily to climate change can take a huge toll. Since majority of the developing nations rely primarily on agriculture for economic development, it is critical to have an accurate understanding of the impact of climate change on agricultural sector.

Nepal is no exception to this rule. With 82.5% of the population living below the international poverty line of $2 per day (World Bank 2003), Nepal is one of the poorest countries in the world. It should be of no surprise that the economy of Nepal is overwhelmingly dependent on agriculture. In the late 1980s, agriculture was the livelihood for more than 90 percent of the population, and while only approximately 20 percent of the total land area was cultivable, it accounted for, on average, about 60 percent of the GDP and approximately 75 percent of exports (Savada, 1991). Although the dependence on agriculture has considerably declined since the 1980's, farming is still one of the primary occupations of people residing in Nepal. Such a heavy reliance on agriculture makes

Nepal's economy very sensitivity to climate variability. It is thus imperative to have a clear and accurate assessment of the climate change impact on Nepalese farmlands to devise policies to make the agricultural sector more resilient to climatic events. In my fourth chapter, I investigate the impact of climate change on agricultural productivity in Nepal by taking into account the extreme weather events.

1.2 Research Design and Data

The second and the third chapters of my dissertation, "*Public preferences for ecosystem services in the Danda River Basin: A Choice Experiment Study*", and "*Water quality avoidance behavior: Bridging the gap between perception and reality*", uses a primary survey data. This section highlights the survey design procedures and presents some descriptive statistics for the survey data that I use on the second and third chapters.

1.2.1 The study site:

The focus of the second and the third chapters of my dissertation is in the city of Siddhaarthanagar in Western Nepal, which is at the crossroad of urban growth and environmental fragility. The city of Siddharthanagar is considered as a major trading city in Nepal and is located on the border of Nepal and India about 170 miles west of the capital city of Kathmandu. As a gateway town next to the World Heritage site of Lumbini (birthplace of Buddha), the municipality of Siddharthanagar is expected to face increased tourism pressure, especially after the completion of a nearby international airport. The Danda river system, which passes through Siddharthanagar is already plagued by household garbage dumping and industrial runoff. Many patches of urban forests, wetlands, pristine vegetation, and potential bird sanctuaries along the river banks are rapidly disappearing. The surface and ground water sources are contaminated, and the air pollution in the city is visibly unsettling. If unchecked, the urban quality of life and human wellbeing are likely to face significant deterioration. These degradations will also have a reverse impact on the social and economic organization in the city itself. Economic, health, biodiversity and sociopolitical implications are all intertwined, and as such, approaching such goals through good evidence-based policy making is the key. To understand the far-reaching consequences of haphazard urbanization on environment health and well-being, we conducted a household survey. The survey was conducted in the urban city of Siddharthanagar, and its two adjacent rural settlements, Basantapur and Bagaha.

1.2.2 Survey Design and Methodology:

The survey design was carried out in two stages:

Stage 1:

The whole study area was divided in 3 strata in such a way that the sampling units within the stratum are as homogenous as possible and sampling units between strata are as much heterogenous as possible. The three strata consist of Siddharthanaga municipality, Bagaha Village Development Committee (VDC) and Basantapur VDC. The sampling area consisted of 28 wards that were partially within the Danda catchment area. We stratified the sample by ward to ensure sufficient geographic spread.

- Further each stratum was subdivided into number of clusters of wards. There is a total of 28 clusters in the 3 strata, which consists of 14,409 households.

Table 1.1: Survey Design						
Strata	Name	No. of households	Number of wards	Number of clusters to be sampled (n_h)	No. of households to be sampled	Over sampling
1	Siddharthanagar municipality	12,497	12	12	520	572*
2	Bagaha VDC	707	8	4	30	90*
3	Basantapur VDC	1,205	8	4	50	90*
	Total	**14,409**	**28**	**20**	**600**	**752**

Stage 2:

- The $n_h$clusters were selected from each stratum with probability proportional to size of households so that the total number of clusters is 20 and households is 600, where n_h is the number of cluster for hth stratum
    - Proportionate stratification: $n_h = \left(\frac{N_h}{N}\right) * n$

  Where, n_h = sample size for the stratum; N_h = population size for the stratum; N= total population size; n = total sample size.

    - Number of household sampled = $\frac{Number\ of\ households\ in\ strata\ i}{Total\ households} * 600$

In total, we surveyed 752 households for the final survey. Enumerators were instructed to take a random route through the wards, stopping at every 5th house for a total of 5 households per enumerators per day. Furthermore, they were asked to interview only household representatives age 18 or older. If a household declined to take the survey, the enumerators would go to interview the corresponding house.

1.2.3 Survey Protocol:

The survey protocol included expert interview, focus-group discussions, debriefing, pilot survey and the final survey. In preparation for the survey, we started with expert interviews as a quick way to obtain information on the survey area. The expert interviews were conducted with the ward[1] personnels of Siddharthanagar municipality; and Bagaha and Basantapur VDC[2]s. These interviews played a vital role in redefining the concrete environmental and health issues in and around Danda River; and the survey questions were modified accordingly.

A focus group discussion was also conducted in PNMHI (Pratiman-Neema Memorial Health Institute, Bhairahawa) with representatives from all three VDC's and municapility. The focus group discussion was conducted on 20 participants that comprised of male and female participants from different locations of the three-study area. This session was valuable as it helped us to make our questions more concrete and actually to gauge the problem we were trying to study from an average citizen's perspective. The focus

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[1] Wards are the smallest denominations and are equivalent to zip codes in US. There are 12 wards in Siddharthanagar municipality and 8 wards each on Bagaha and Basantapur VDCs.

[2] Village Development Committee

group provided some insightful comments and we modified our survey as per their suggestions. After the focus group, the next step undertaken was a one-on-one debriefing session with few individuals. Each selected respondent went through the survey by reading it aloud to themselves and answering all the questions. We recorded the time taken to complete each question and at the end they provided comments on the survey in general. This process played an important role in helping us understand how potential respondents would see the survey and the complications that could arise.

Fig 1.2: Focus group discussions

After the three steps mentioned above, the first pre-test survey was conducted on 50 randomly sampled households in five wards of Siddharthanagar; and 3 wards each from Basantapur and Bagaha. We selected 30 households for the municipality and 10 households each for the VDCs. The result from this survey was used to estimate some preliminary result, primarily to understand whether respondents were properly understanding survey questions. While the results did not look too out of ordinary, there were some problems in respondents understanding the choice experiment section for Danda river in the survey. As a result, the survey was slightly modified, and another pretest was undertaken with 50 different household samples with the same logistics as the first pretest survey. In total, we had to conduct four rounds of pre-test survey before we were confident that the respondents clearly understood all the questions asked.

After the four round pretest survey, the final survey was conducted between June 05 – July 16, 2016 to a total of 752 respondents across Siddharthanagar, Basantapur and Bagaha. The survey was administered in *Nepali* and *Maithili* language by 8 college level students that were trained for 3 days in survey techniques. Enumerators used a scripted introduction to assure that each respondent received the same amount of introductory information. The enumerators were also given a GPS device to record the household coordinates of each respondent. Finally, each household that undertook the survey was presented with a detergent powder as a gift for their time.

Figure 1.1 presents the map of the study area with the households that were surveyed.

1.3 Descriptive Statistics:

In this section, I provide some basic statistics on the sample respondents. The preliminary evidence from the survey data suggests that households value the Danda river system. More than 84% of the households surveyed considered preservation of Danda river to be vital; and only 71% of the residents in Siddharthanagar believed that the restoration of Danda River was the sole responsibility of the government (Figure 1.3 and 1.4).

Households were willing to make either a monetary contribution or to volunteer to help preserve the Danda river ecosystem. Figure 1.5 indicates that households in Siddharthanagar are willing to pay (WTP) on average Rs.400/year help restore Danda river. Even the communities further away from Danda River like the households in Bagaha VDC were WTP about Rs.330/year Figure (1.5). We also asked whether households wanted to contribute time by volunteering rather than making a monetary contribution for the river conservation. There were substantial number of households across all three locations that were willing to volunteer, but the biggest contributors of time were found to be in the Bagaha region where 45 % of the surveyed households were willing to volunteer rather than giving money (Figure 1.6).

Among the many ecosystem services that Danda provides, one provision service available from the Danda river is water for irrigation. Figure 1.7 shows that more than 25% of the farmers in our survey used Danda water solely for irrigation purposes. Moreover, households in general think that improvement in Danda River can lead to benefits in the form of improved agriculture, more access to fisheries, and would also positively contribute to the health of the people (Table 1.2). The indirect benefits of Danda river is dependent more in the overall health of the river. A better Danda river would not only provide cultural and aesthetic value, but would also help flood risks to be managed, and also prevent soil erosion if there is enough vegetation around the banks to stabilize the soil.

Moving on towards the households drinking water behavior, Figure 1.8 shows the distribution of water sources for the three areas: Siddharthanagar, Bagaha and Basantapur.

Households in Siddharthanagar primarily relied on private taps, with tube well-being the close alternative for the majority of the households there. In Bagaha and Basantapur, the majority of the households used tube-well as their primary source of water. Figure 1.9 shows the water treatment behavior of the households, and the graph suggests that in all three areas, households that used private taps were more likely to treat their water. Conversely, households using deeper sources like tube-well and boring were less likely to treat their water. However, across all three areas, households using public taps were the ones that were least likely to treat their drinking water.

To get an idea on the households' socioeconomic characteristics, Table 1.3 presents the distribution of education levels of the individuals. The general sample was quite literate with only 17% of the households having little to no education. When we look at the education distribution of households that were residing near the Danda river (within 10 minutes walking distance), the distribution of education level is still similar to the overall sample. The majority of the population had at least a high school education, while individuals with a bachelor's degree or higher were the least represented group in both, the overall sample and also households within 10 mins of Danda. Table 1.4 presents the distribution of households by based on the ethnic groups. The majority of households in the overall sample, as well as those that reside within 10 minutes of Danda river were both from the Madhesi communities. Brahmins and Chhetris ethnic group comprised of 20% of the population that live within 10 mins of Danda, while Dalits were the lowest represented group in both the overall sample and also among the households within 10 mins of Danda.

Figure (1.10) presents the wealth distribution of households based on their possession of different durable goods. The asset index was created using the principal component analysis (PCA) following a methodology similar to Vyas and Kumaranayake, (2006). The durable goods considered were whether a household possessed assets like radio, television, telephone, fan, air conditioner, bicycle, motorcycle, car, refrigerator, washing machine, and computer. Households with a greater number of assets are represented by higher score factors. It is evident from the figure that wealth is skewed towards the left with most households owning less assets (poor households). On the other hand, there are few households that own various kinds of assets, and they are considered as the wealthy households.

1.4 Contribution of my dissertation

My second chapter, "*Public Preference for Ecosystem Services in the Danda River Basin: A Choice Experiment Study*" employs a discrete choice experiment (CE) method to explore preferences for freshwater ecosystem services. I use geocoded primary survey data from 637 households to explore the potential for sustainable management of the Danda River Basin in Nepal. The major contributions of this study are twofold: First, I account for the households that exhibited lexicographic preferences, and households that made near random choices. This is done by extending the Multinomial logit model to accommodate preference and scale heterogeneity in the data. I assume that one source of randomness arises from the degree of certainty among the households when they made a choice, and model it by allowing the mean of the scale parameter to differ across households according to their stated uncertainty levels. Second, I examine the local spatial welfare distributions by employing the Getis-Ord hot spot analysis, and as a result, deviate from the global continuous distance-decay patterns commonly assumed in stated preference (SP) studies.

The findings indicate substantial demand for the Danda ecosystem services. Respondents were willing to pay (WTP) $17.06/year on average for the highest quality of river water and $13.46/year to introduce vegetation in the riverbanks. One noteworthy result was a robust support for local governance with the households preferring a community-based management of the river ecosystem. This finding highlights the need for policymakers to decentralize their management to the local communities which could result in greater community participation for the sustainable conservation of common-pool resources. The inclusion of preference uncertainty in the estimation process did not substantially alter the mean marginal WTP estimates, but it did produce tightened confidence intervals relative to other models. Finally, the analysis of spatial distribution indicated localized pockets of statistically significant hot and cold spot areas for the different ecosystem services. In particular, people in the urban area seem to derive benefits from the river for recreational activities, while the rural population desired improvements in the Danda water quality for agricultural activities.

Drinking water quality remains a significant issue and a source of serious health concern in the developing world. In my third chapter, *"Water Quality Avoidance Behavior: Bridging the Gap between Perception and Reality"*, I use a primary survey data to investigate households' water averting behaviors in Nepal. In the analysis, I place a particular emphasis on investigating whether the information gap that exists between the households’ perception of their drinking water quality and the actual water quality level could explain the averting behaviors. Thus far, the majority of previous studies that have examined households’ water handling behaviors have primarily converged either on exploring the influence of information dissemination on changing behaviors or examining the role of perceptions in explaining the averting behaviors. However, past studies have not really investigated averting behaviors by taking into account both, water quality information and household perceptions. My study attempts to fill that space by exploring whether the information gap that could exist due to the difference between perceived and actual water quality levels could influence the adoption of environmental risk-averting behavior.

The findings indicate that while the perception of water quality affects the water averting behavior, the divergence between perception and reality could also be an important element in a household’s decision to employ water treatment measures. Households that considered their water to be risky were 6 percentage points more likely to treat their water than households otherwise. However, households that considered their drinking water be risky and this perception was confirmed through the presence of *Escherichia coli* (E. coli) bacteria in the households drinking water were 25 percentage points more likely to adopt water averting measures. Results also suggest that the water source, education level, and the taste of the drinking water drives the averting behavior as well. These findings are indicative of the acute need to focus on accurate information dissemination and to implement policies targeted towards improving the community’s perception on their built environment and health as one measure to minimize water borne illnesses in the developing world.

My fourth chapter, *"Assessing the impact of climate change on farmland values in Nepal"* employs a hedonic approach using the Ricardian model to explore the impact of climate change on agricultural productivity in Nepal. This paper differs from previous work on Ricardian approach literature in that the effect of climate change is analyzed by treating the choice of irrigation as endogenous. There have been very few works that have employed the Ricardian approach in Nepal, and none that treats the choice of irrigation as endogenous. We build an endogenous irrigation model to recognize the potential of sample selection bias (Heckman 1979). In the first stage, we estimate the probability of irrigation including climate, district flows, and other exogenous variables. In the second stage, we estimate the land value for the rainfed and irrigated farming including a sample selection correction term. We test this model using a sample of over 1165 plots across 27 districts in Nepal. The empirical results reveal that the choice of irrigation is endogenous. The results indicate that Nepalese farmlands are sensitive to climate change. Irrigated farmlands were found to have a higher land value when the temperature and rainfall increased during summer season. Dry lands, on the other hand had a reduction in land value due to an increase in temperature and rainfall during spring season. This result indicates that irrigated farmlands can be an effective mechanism to protect land values from changes in rainfall and temperature.

1.5 Figures and Tables

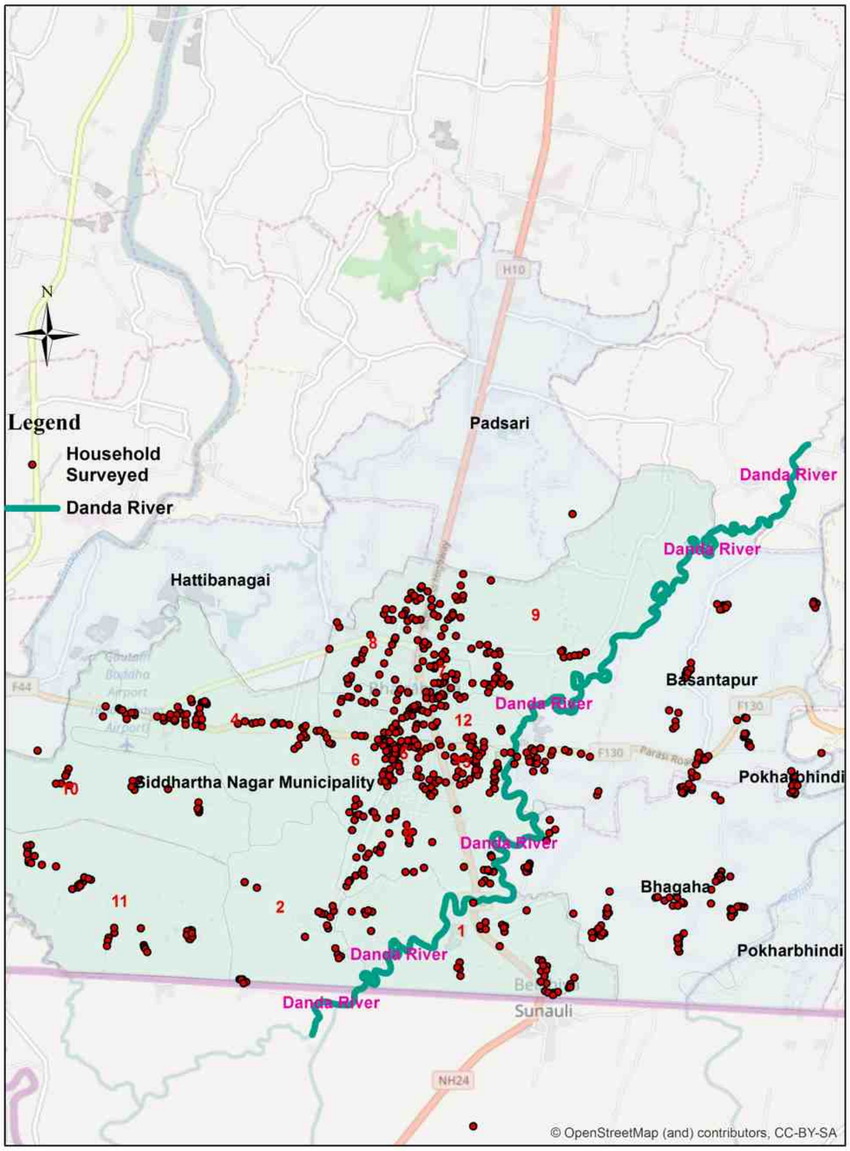
Figure 1.1: Map of the Study Area


Figure 1.3: Percentage of population that believe government alone to be responsible for cleaning Danda River

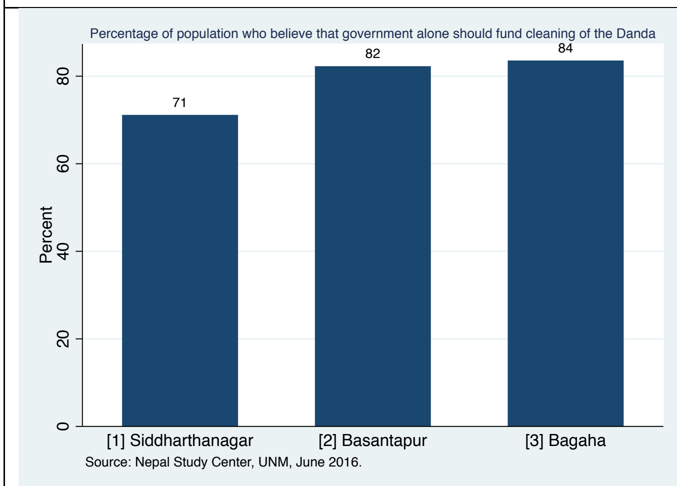


Figure 1.4: How important is Danda River to you and your family?

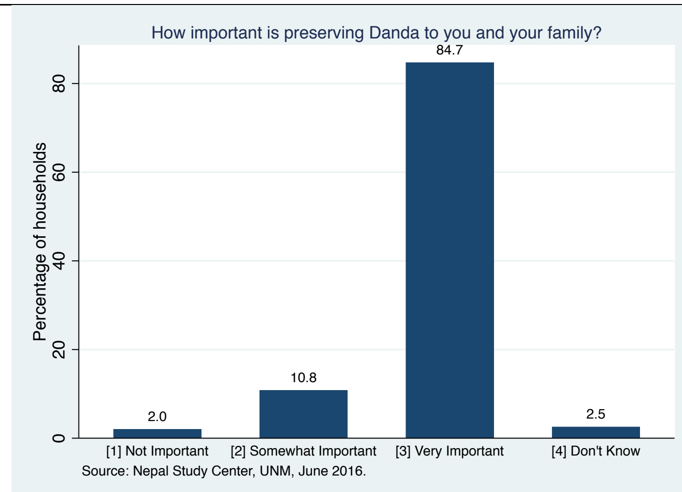


Figure 1.5: Willingness to Pay to clean Danda River

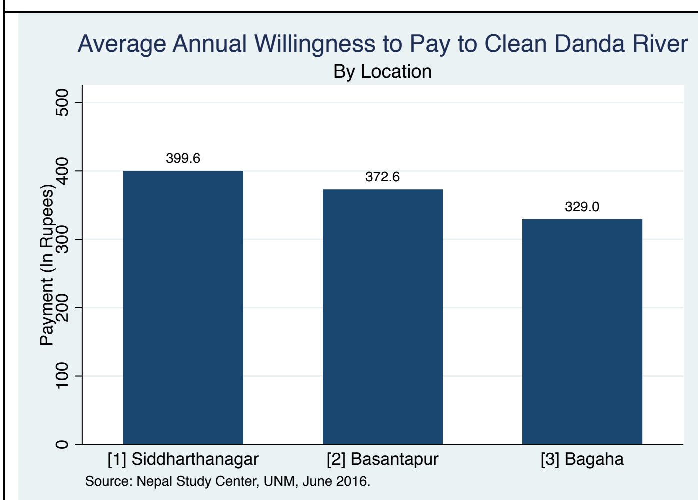


Figure 1.6: Willingness to Volunteer to clean Danda River

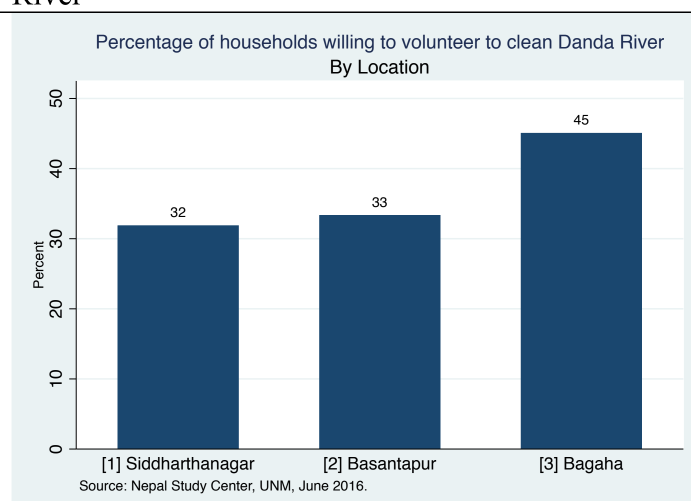


Figure 1.7: Danda River as a mode of irrigation used in farmlands

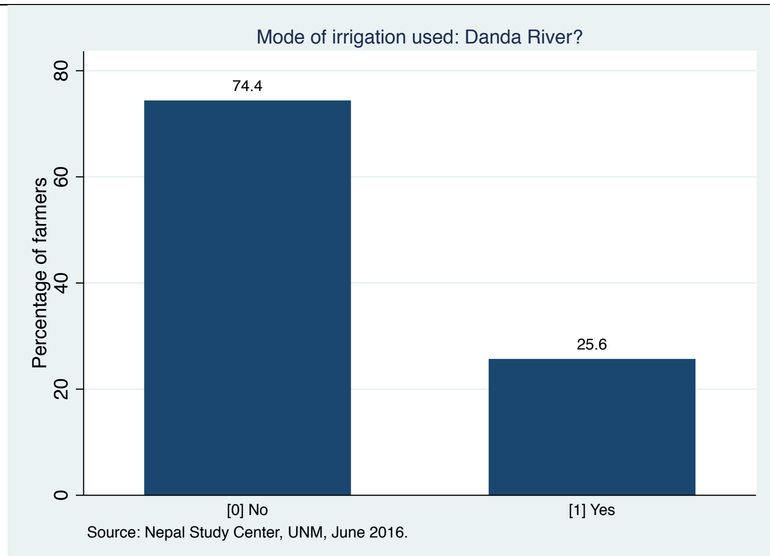


Figure 1.8: Major Drinking Water Source

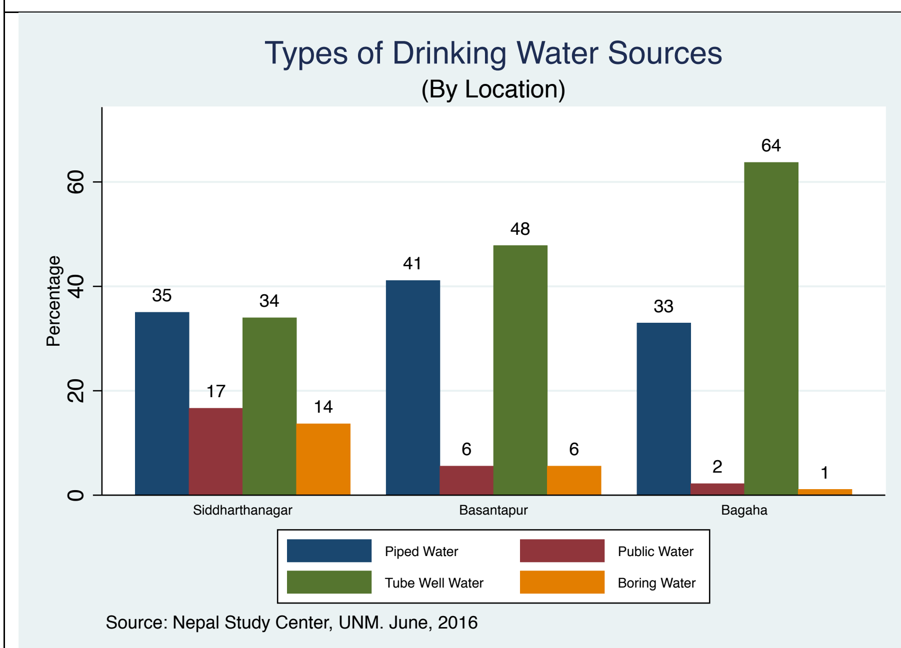


Figure 1.9: Water treatment behavior

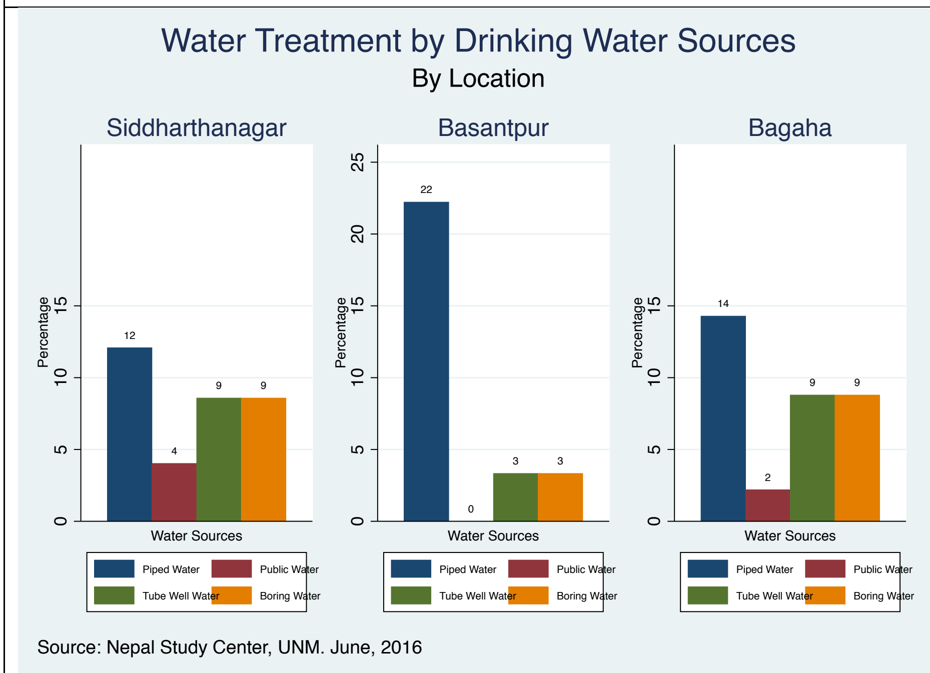


Figure 1.10: Distribution of wealth as defined by assets of the household

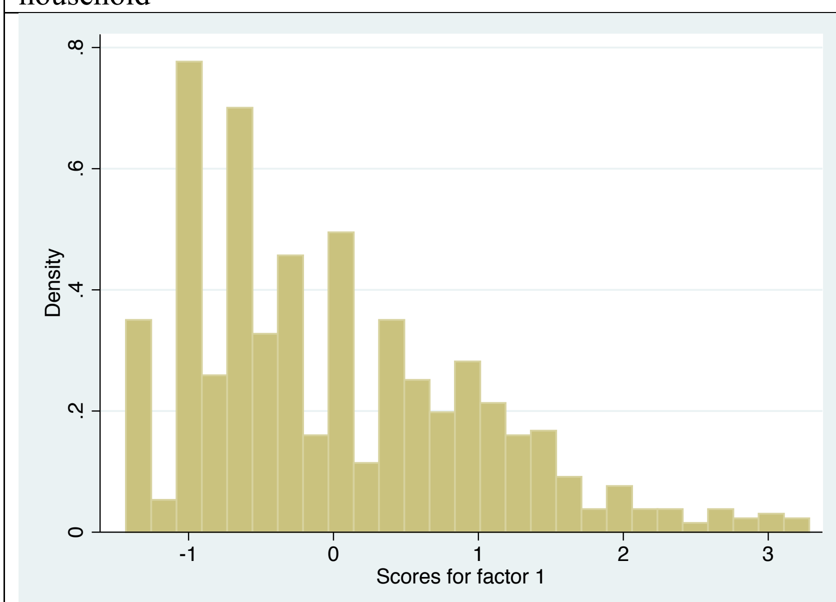


Table (1.2) If Danda river was restored, do you believe households would benefit in the form of:-		
	Benefit	**No Benefit**
Agriculture	97.34%	2.66%
Fishery	89.49%	10.51%
Health	91.76%	8.24%
Recreational activities	92.29%	7.71%
Drinking water	52.13%	47.87%
Land Valuation	85.51%	14.49%
Culture	89.36%	10.64%

Table (1.3): Distribution of education level by (i) Overall sample; (ii) Households living 10 mins of Danda				
	Overall sample		**Households living 10 mins of Danda**	
	Number of individuals	**Percentage**	**Number of individuals**	**Percentage**
Little or no education	133	17.69%	34	20.86%
High School	146	19.41%	34	20.86%
Some College	130	17.29%	23	14.11%
Bachelor & Higher	90	11.97%	19	11.66%

Table (1.4): Distribution of Caste by (i) Overall sample; (ii) Households living 10 mins of Danda				
	Overall sample		**Households living 10 mins of Danda**	
	Number of households	**Percentage**	**Number of households**	**Percentage**
Brahmin & Chhetri	171	22.74%	32	19.63%
Madhesi	373	49.60%	85	52.15%
Dalits	55	7.31%	9	5.52%
Janjati	149	19.81%	36	22.09%

Chapter 2: Public Preference for Ecosystem Services in the Danda River Basin, Nepal: A Choice Experiment Study

2.1 Introduction

Freshwater systems have historically been the linchpin of urban centers; however, they are also considered to be the most endangered ecosystems in the world (Dudgeon et al., 2006). As rural landscapes are transformed into cities at an accelerating rate (Heilig, 2012), these transformations can have a profound negative impact on the ability of river systems to provide the ecological and social services upon which human life depends (Postel & Richter, 2003). High-profile examples like the historic “flaming Cuyahoga River of Ohio,” the Ganges River in India, and the Yellow River in China encapsulate the global concern over urban risks to river systems. A better management of these productive ecosystems could provide an array of ecological functions and services, ranging from biodiversity, water quality maintenance, and flood and flow controls, to recreational and aesthetic value.

One current and alarming example of freshwater degradation is in the city of Siddharthanagar, Nepal, where unplanned urban sprawl and a lack of proper sanitation systems have turned its once pristine Danda River into a channel of sewer drainage. The Danda River (27.48^0 N, 83.46^0 E) runs through the heart of Siddharthanagar, a rapidly growing city on the Nepal-India border located 170 miles west of the capital city of Kathmandu, Nepal. The city of Siddharthanagar is also the gateway to a major tourist destination site: The United Nations Educational, Scientific and Cultural Organization

(UNESCO) world heritage site of Lumbini and the birth place of Buddhism. One of the many threats of urban sprawl in Siddharthangar is the diffuse pollution dumped into the Danda River, where poor drainage systems carrying the road runoff from the surrounding residential and industrial zones are gradually worsening the river ecosystem.

An environmental impact assessment carried out on Lumbini (including the city of Siddharthangar) affirmed that unregulated discharge of waste by households and industries had resulted in excess deposits of chemicals such as dissolved oxygen, phosphates and nitrates in the freshwater rivers in the region (IUCN, 2012). An inevitable consequence of the deteriorating freshwater systems has been the rapid loss of biodiversity and aquatic species in the Danda Basin. Furthermore, irrigation from these water sources are no longer possible, and people can no longer engage in water-based recreational activities they once enjoyed. The severity of this issue has had a rippling effect on the local economy, as various community segments, in particular the fishermen and the farming populations, have been forced to take up to new activities to sustain their livelihoods (IUCN, 2012). Moreover, an unhealthy Danda River could also deter the record influx of tourists that come to Lumbini via Siddharthangar every year (Nyaupane et al., 2014), placing a significant burden on the economy of the country itself.

The Danda ecosystem constitutes a valuable natural resource, in economic, cultural, aesthetic, scientific, and educational terms to the Nepalese people. The intertwined nature of the Danda River with the communities that rely on it necessitates a thorough analysis to ensure the well-being of the health of the river and its surrounding riparian system. The objective of this paper is to investigate the potential for a sustainable management of Danda River and its ecosystem. As such, we explore people's valuations and preferences for improved ecosystem services in the Danda River Basin, Nepal. The major contributions of this study are threefold. First, this paper adds to the limited number of choice experiment studies that confront the issue of sustainable management of urban river systems in developing countries and is the only one to focus on the Danda River Basin in Nepal. Second, from an empirical point of view, we use the Generalized Multinomial Logit (GMNL) model and incorporate respondents' preference uncertainty in a bid to increase the precision of the marginal willingness to pay (MWTP) estimates. Third, we explicitly account for spatial heterogeneity by employing a hot spot analysis, and as a result, deviate from the continuous distance-decay method commonly assumed in stated preference (SP) studies.

We find evidence of substantial demand for the Danda ecosystem services. The results suggest that respondents are willing to pay NPR. 1,777 ($17.06/year; US 1$ = Nepali NPR.103 conversion rate, as of June 12, 2017, used throughout) for the highest quality of river water, while the MWTP to protect the riverbank to 300 feet is NPR. 325 ($3.15/year), and NPR. 1,387 ($13.46/year) to introduce vegetation in the riverbanks. The inclusion of preference uncertainty in the estimation process resulted in an improved model fit and produced tightened confidence intervals for the marginal MWTP estimates. We find a presence of statistically significant hot and cold spot pockets for different ecosystem services, indicating local spatial heterogeneity. In particular, people in the urban area seem to derive benefits from the Danda for recreational activities, while the rural population desires improvement in Danda water quality for agricultural purposes. Finally, we observe that the public prefers a community-based management of the Danda River. This finding highlights the need for policymakers to decentralize their management to achieve community participation for sustainable conservation of natural resources starting from the grassroots level.

2.2 Critical Review and Synthesis of the Literature

An extensive body of literature has been developed since the 1960s to assess goods that cannot be traded in the market, with stated preference and revealed preference methods being the widely used approaches. Within the SP methods, the choice experiment (CE) technique has seen a huge surge in the environmental and health literature in recent years (Mahieu et al., 2014), largely because of its flexibility to allow for welfare analysis of multiple scenarios. A field that has witnessed a sustained interest in CE application is the management of wetlands and river systems. One of the earlier studies to employ CE in a developing country context was done by Othman et al. (2004) to explore the non-use values and to determine the optimal management strategy in the Matang Mangrove Wetland, Malaysia. The findings suggested that households preferred the forested area and migratory bird species in the wetland, however, the valuations were found to differ based on the management scenarios. Do and Bennett (2009) used CE to explore the non-market value of biodiversity conservation program in the Tram Chim National Park Wetland, Vietnam and found that preservation could generate net social benefits between US$ 0.15 – $0.96 millions.

There have been other notable CE studies that explore the river ecosystems, both, in the developed and the developing world, including those by Carlsson et al. (2003) in exploring the perceived values of wetlands in Sourthern Sweden; Hanley, Wright, and Alvarez-Farizo (2006) in investigating public preference for river ecology in the United Kingdom and Scotland; Alvarez-Farizo et al. (2007) in examining the Cidacos River in Spain; Birol et al. (2006) in exploring potential for sustainable management of the Cheimaditida wetland in Greece; Birol and Das (2010) in estimating preference for improved wastewater treatment in the River Ganga, India; and Volmer et al. (2015) in investigating the valuation for the Ciliwing River in the urban city of Jakarta, Indonesia.

In spite of the numerous CE studies on river ecosystems, most fail to explore the spatial distribution of the welfare estimates. Even studies that incorporate the spatial dimension of MWTP estimates largely depend on self-reported measures (e.g., self-reported distance from a site being valued), which can be imprecise. The assumptions used to explore the spatial heterogeneity can also be another source of concern. For instance, many CE studies commonly assume a decaying MWTP as a monotonic function of distance or discrete thresholds over geopolitical boundaries (Bateman et al., 2006; Brody et al., 2004), an assumption that has been criticized as being unrealistic (Bateman et al., 2006; Loomis, 2000). In fact, spatial patterns for use and non-use values could exist at a relatively local level that traditional approaches like continuous distance-decay methods with global assumptions might fail to capture. These consequences could lead to studies falsely concluding an existence of spatial homogeneity when heterogeneity could in fact exist at a local level.

One of the foremost CE analyses to explicitly model the spatial phenomena was undertaken by Campbell, Hutchinson, and Scarpa (2009) to explore non-continuous spatial patterns of MWTP estimates by using kernel density estimation (KDE) and kriging interpolation methods. A more robust method to explore the spatial dimension through a direct test of statistical significance is an analysis of hot and cold spots using local indicators of spatial association (LISA) (Anselin 1995; Rogerson, 2001). Hot spot analysis using the LISA method is common in other disciplines and has been employed to explore phenomena in crime analysis (Chainey, Tompson, & Uhlig, 2008), tourism (Yang & Wong, 2013), disease mapping (Jeefo, Tripathi, & Souris, 2010), transnational terrorism (Braithwaite & Li, 2010), and traffic accidents (Gundogdu, 2010), amongst others.

In regards to CE studies, Johnston and Ramachandran (2014) proposed a method to evaluate localized welfare patterns using LISA to address the migratory fish restoration program in the Pawtuxet Watershed of Rhode Island, United States. They discovered several significant hot and cold spot areas at local levels for different attributes which were not identified using the continuous distance-decay assumption. Other applications of hot spot analysis using the LISA method in a CE setting have been employed by Meyerhoff (2013) to investigate people's preference for wind turbine development in Westachsen, Germany, and by Johnston, Wallmo, and Lew (2015) to explore spatial heterogeneity in large sample areas. A common theme across these hot spot analysis studies using CE is the necessity to employ novel techniques to analyze spatial patterns that may be overlooked using the traditional methods such as the continuous distance-decay assumption.

While the failure to explicitly account for spatial heterogeneity can result in unreliable welfare estimates, a different issue in CE studies can stem from the inherent assumption that respondents know their preferences and are able to accurately gauge their utility from the goods presented to them. In reality, it is likely that respondents may not present an accurate reflection of their true preferences, which could occur through numerous possibilities (e.g., lack of expertise in the good of study; difficulty in responding to hypothetical scenarios; general laziness or inattention paid on choice tasks; cognitive burden etc.). These situations could give rise to respondent preference uncertainty, which can affect response patterns and result in biased, if not the valuation estimates, then at least the variance estimates and the inferences made (Li & Mattson, 1995). Many CE studies have thereby tried to incorporate preference uncertainty to reduce the bias in welfare estimates. One of the earlier CE studies to explore preference uncertainty was by Olsson, (2005). They used the recoding approach to incorporate uncertainty and found that respondents who were certain of their choices had a higher MWTP relative to less certain respondents. A more detailed inspection of certainty calibration in a CE setting was done by Lundhede, Olsen, and Jacobsen (2009), where they examined several methods to handle self-reported preference uncertainty. Their novel approach was to explicitly model uncertainty by integrating it as a systematic variation of the scale parameter. They argued that the recoding approaches cannot satisfactorily handle uncertain answers in a CE setting, a finding that has also been verified by Kosenius (2009); and Beck, Fifer and Rose (2016). Their approach to incorporate uncertainty as a function of the scale parameter produced narrower confidence bands and led to a reduction in unexplained variance; however, it did not substantially change the mean of the MWTP estimates relative to the baseline model. A similar approach to model uncertainty in a CE setting has also been employed by Beck, Rose, and Hensher (2013); Borger (2016), and by Tu and Abildtrup (2016). The general findings of the aforementioned studies are that more certain choices can reduce scale heterogeneity relative to choices where the respondents are uncertain.

This paper explores the potential for improved ecosystem services in the Danda River Basin by taking into account the highlighted concerns in regards to spatial heterogeneity and preference uncertainty. The investigation for the presence of spatial heterogeneity is conducted by employing the LISA hot spot analysis and the kriging interpolation method. Similarly, in a bid to achieve improved welfare estimates, we incorporate respondents' preference uncertainty by specifying it to be a function of the scale parameter in the GMNL model. The latter analysis assumes that respondents' stated uncertainty reflects their true certainty level and follows a methodology similar to Lundhede, Olsen, and Jacobsen (2009).

2.3Data and Methods

This study uses primary data from a household survey that was conducted in the urban city of Siddharthanagar municipality *(n=457)* and its two neighboring rural areas, Bagaha Village Development Committee (VDC; *n=89)* and Basantapur VDC *(n=91)*. The CE section of the survey was completed by 637 households, representing an effective response rate of about 90%. Each respondent completed three choice tasks for a total sample of

1,855[3] observations. We made efforts to deliver clear and equal information to all the respondents using focus group discussions and thoroughly pre-tested questionnaires[4]. The survey[5] was administered in *Nepali* and *Maithili*[6] languages, and the respondents were given ample time to complete the choice tasks. Figure 2.1 presents a map of the study area along with the households that completed the CE survey.

The CE study was developed to explore the potential for a sustainable management of the Danda River's ecosystem, and the good to be valued in this study was the river ecosystem services. The final CE survey consisted of three choice sets with three alternatives (two policy options, plus a status quo option) for all the respondents. Additionally, each policy option contained six attributes that differed in their levels over the set of presented policy alternatives. Table 1 summarizes the attributes with their levels as well as the status quo option. The choice sets were designed using the SAS macro (%ChoiceEff), choosing from an orthogonal array fractional main effects design (Holmes

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3 Although the total sample for 637 households with three choice sets should be 1,914, there were few households with missing observations in at-least one (and not more than two) choice sets. We excluded those choice sets from the analysis and the remaining sample size was therefore 1,855.

4 The focus group comprised of about 20 individuals from different backgrounds, and were recruited on a 'friend-of-a-friend' approach. These participants were invited to the Prateema-Neema Health Institute (PNMHI) campus in Siddharthangar to conduct the focus group discussions (FGD). We presented some background information on the Danda River and informed them about a potential management plan to conserve the Danda ecosystem. The FGD was followed by debriefing and pre-test surveys. The pre-test survey lasted for five different rounds by modifying the information presented in each succession. It was conducted on 50 households from the study area in each round.

5 The households for the survey were selected using the stratified sampling technique. The enumerators were instructed to take a random route through the wards, stopping at every 5th house. These enumerators were trained for face-to-face interviews and to adequately address the cognitive burden associated with choice sets that were identified during the FGDs and debriefings. They used a scripted introduction to assure that each respondent received the same amount of introductory information, and were also equipped with a global positioning system (GPS) device to record the location of each respondent household.

6 Maithili is a local language common among a certain section of the people in the study area.

and Adamowicz, 2003; Kuhfeld, 2005; Louviere et al., 2000). The choice sets were obtained using a saturated design of 24 choice sets, which were blocked into eight versions of three cards during the survey. An example of a choice question is presented in Figure 2.2, where ‘Management Package’ A and B represent improvements with respect to the baseline situation (Management Package C).

2.3.1 Attributes and Levels Selection

The ecosystem service attributes used in the study are comprised of ecological, social, and economic factors to reflect the variety of benefits generated by the river. The ecological factors are defined by the quality of the river water, the area of riverbank protected, and the trees planted around the banks. The first attribute, *river water quality*, refers to the general health of the river. The levels were derived from a modified “water quality ladder” that was first implemented by Carson and Mitchell (1993), which allowed us to translate technical water quality measures to simple categories that non-experts could understand. The water quality ladder comprised of cleaning the water to be suitable for “*boating;*” “*boating and fishing;*” and “*boating, fishing, and irrigation*”. The first two levels capture the aesthetic and recreational benefits of the Danda River; while the final level includes the agricultural benefits derived from the Danda.

The second ecological attribute, *riverbank protection*, captures the number of feet of Danda riverbank to be protected from urban encroachment. The status quo level for this attribute is 50 feet of riverbank protection, following a law mandated by the local government of Siddharthanagar in early 2016. The ecological literature recommends an optimal buffer width of 300 feet (Hawes et. al, 2006), which is the maximum level used for this attribute. The final ecological attribute, *the percent of riverbank area planted with trees*, is important not only to prevent the sediments and pollutants from reaching the river, but also to serve as a natural and sustainable habitat for wildlife and birds.

The attributes used to capture the social factor includes *the provision of a river monitoring and educational program*, and *the regulatory mechanism*. The aim of the monitoring and educational program is to involve student volunteers from different schools in Siddharthangar in regular testing of pollutants in the river. Often known as *citizen science*, the involvement of the community in the scientific data collection can be cost effective, and should also generate curiosity in students to learn more about the Danda River. But, more than that, such community involvement can put an onus on the community stakeholders to be the champions of the cause. The second social attribute, *regulatory mechanism,* refers to the body responsible for overseeing the collected funds and the management of the Danda project. The rational for the latter attribute was also to explore the attitude of the local public in implementing a community-based management approach to maintain the Danda River.

The final attribute used is a monetary one and is included to estimate respondents' marginal willingness to pay (Louviere et al., 2000). In regards to the payment mechanism, the commonly used mechanism to elicit price response in environmental SP studies like changes in utility bills (e.g., water or electricity bills), or taxes (e.g., land, property, income tax etc.) was not feasible in our study area. For one, the majority of survey respondents were not connected to a municipal water supply. There is also a severe problem with electricity outage, which has forced households to rely on alternative sources of electricity like solar power. Taxes were not found to be a good instrument either, as many residents simply did not pay taxes, a drawback pervasive in many developing countries. Given the lack of a viable natural mechanism to collect fees, we consulted with key informants, local officials, and experts to ascertain the best mode of raising funds. We also discussed a five-year plan with these stakeholders to identify a concrete strategy for the implementation and management of the project. The payment vehicle was ultimately decided to be applied in the form of an annual payment of a "*Danda River management fee*" for five years. The absence of a natural payment mechanism in different parts of Nepal has in fact compelled the use of donation as a payment vehicle in several SP studies (Atreya, 2007; Borghi et al., 2007; Dror et al., 2014; Katuwal, 2012; Poudel and Johnsen, 2009).

2.4 Theoretical and Empirical Framework

2.4.1 *Random Utility Model*

The conceptual economic frameworks for choice experiments have their origin in the conjoint analysis, which shares commonalities with Lancaster's (1966) modern consumer theory. Discrete choice models are generally derived under the assumption that the decision-maker maximizes their utility. According to the Random Utility Maximization (RUM) theory, an individual i facing a choice among j alternatives is assumed to obtain utility U_{ij}. This utility is comprised of two components: a systematic observable component V_{ij}, and a stochastic component e_{ij} that is random and unobservable. This utility is given as:

$$U_{ij} = V(Z_{ij}, X_i) + \varepsilon_{ij} \tag{1}$$

The component $V(Z_{ij}, X_i)$ relates to the measurable component of the utility and should increase with desirable characteristics. The parameter Z_{ij} captures the attributes of the alternatives available to the individual, while X_i represents the characteristics of the individual. The respondent i is assumed to choose alternative j over k only if the utility received from j is greater than the alternative k, i.e., $U_{ij} > U_{ik}$.

The basic utility specification for the three management scenarios in this study can be stated as:

$$\begin{aligned} U_{ij} &= \beta_1 \text{ASC} + \beta_2 Quality_{All} + \beta_3 Quality_{Boat\&Fish} + \beta_4 Quality_{Boat} + \beta_5 Riverbank_{150} \\ &+ \beta_6 Riverbank_{300} + \beta_7 Trees_{40} + \beta_8 Trees_{80} + \beta_9 Monitoring \\ &+ \beta_{10} Regulation_{Muicipality} + \beta_{11} Regulation_{Government} + \beta_{12} Cost + \varepsilon_{ij} \end{aligned} \tag{2}$$

where, *Quality*, *Riverbank,* and *Trees* are the three ecological attributes; *Monitoring* and *Regulation* are the social attributes; and *Cost* is the monetary attribute of the CE study. The ASC is an alternative-specific constant that captures the impact on utility for a non-status quo option from factors that are not included in the model (i.e., status quo bias), while β's are the marginal utilities (taste parameters) to be estimated. One primary purpose of this study is to derive the welfare effects of changes in river ecosystem attributes, which is done by estimating the MWTP estimates. The WTP for a marginal change in the level of provision of each ecosystem attribute can be obtained by dividing the coefficient of that attribute by the coefficient of the cost attribute (Louviere, 2001).

2.4.2 *Empirical Framework*

The empirical framework to estimate Equation (2) was conducted using various models, with the conditional logit (CL) model used for the baseline specification. The key assumption of the CL model is that errors are independent of each other, i.e., the stochastic term of the utility for one alternative is not related to the stochastic term for another alternative (McFadden, 1973). While the CL model is applicable in certain situations, it has restrictive assumptions that limit its efficacy to portray an accurate representation of reality. First, CL models can account for taste variations with respect to observed variables of the decision maker, but, if tastes vary with unobserved variables or purely randomly, the latter variations cannot be incorporated into CL models. Second, the CL model implies proportional substitution across alternatives, which is referred to as the independence of irrelevant alternatives (IIA) property. We formally investigate the IIA property through the Hausman and Mcfadden (1984) IIA test in our study. The second model we estimate in our analysis is the Random Parameter Logit (RPL) model. The RPL model is an extension of the standard CL model, and it allows for preference heterogeneity through random taste variation, unrestricted substitution patterns, and correlation in observed factors over time (Train, 2009). In the RPL model, we specified the cost attribute to be fixed (Revelt and Train, 2000; Rudd, 1996), while all other attributes including the ASC are assumed to be random and follow a normal distribution.

Even though the RPL model has garnered widespread attention, it has also received criticisms because of its limitations to account for scale heterogeneity (Louviere and Eagle, 2006; Louviere and Meyer, 2008; Louviere et al., 2008). These literatures argue that the normal mixing distribution commonly assumed in the RPL application is mis-specified, and the preference heterogeneity captured by random parameters could be better described by the scale term in some contexts. The scale heterogeneity accounts for the fact that choice behavior might be more random for some individuals than others. One source of randomness in our dataset could arise from individuals' varying degrees of certainty, which is probable because of the complexity of the choice task; and the number of attributes and levels present in the study. The third model we estimate is the GMNL model, proposed by Fiebig et al. (2010). The GMNL model is an extension of the RPL model that can accommodate both the scale and the residual taste heterogeneity. In the GMNL model, the scale parameter σ_i is no longer fixed to one, unlike the case of the CL and RPL model. The parameters in the GMNL model vary across the individuals according to:

$$\beta_i = \sigma_i\beta + [\gamma + \sigma_i(1-\gamma)]\eta_i \tag{3}$$

The specification of β_i in (3) distinguishes it from the CL and the RPL models. Now, β_i depends on a constant vector β; an individual specific scale of the idiosyncratic error term σ_i that proportionally scales β up or down for each individual i; a parameter γ that governs how the variance of η_i varies with scale; and a random vector η_i which captures the residual taste heterogeneity and is distributed MVN (0, Σ). The distribution of the scale parameter, σ_i, in our GMNL model follows the standard assumptions of Fiebig et al. (2010) where the domain of σ_i is set to be positive by assuming an exponential distribution with standard deviation τ and mean $\bar{\sigma}$[7]:

$$\sigma_i = \exp(\bar{\sigma} + \tau v_i) \quad ; \quad v \sim N(0,1) \tag{4}$$

As τ increases, the degree of scale heterogeneity increases. Finally, in addition to allowing the distribution of the scale parameter to follow equation (4), we also assume that the mean of scale differs across individuals depending on their stated certainty level. This represents the fourth and final model used in this study, i.e., the GMNL model with preference uncertainty, and it takes the following form:

$$U_{ijt} = \left(\beta_{0j} + \eta_{0ij}\right) + [\sigma_i\beta + \gamma\eta_i + \sigma_i(1-\gamma)\eta_i]X_{ijt} + \varepsilon_{ijt} \tag{5}$$
$$\sigma_i = \exp(\bar{\sigma} + \delta_1 certain_i + \delta_2 uncertain_i + \tau v_i)$$

where, $\left(\beta_0 + \eta_{0ij}\right)$ is the vector of ASC with β_0 treated as random but unscaled[8] parameter for the estimation in both the GMNL model. The ecosystem attributes are captured by the vector X_{ijt} and all attributes excluding cost are treated as random parameters as in the RPL model. The cost parameter is assumed to be fixed, since getting an empirical positive value for the distribution of MWTP estimates when cost is treated as a random parameter is unfeasible (Rambonilaza & Brahic, 2016). In the GMNL with preference uncertainty, we

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7 Fiebig et al. (2010) proposed normalizing the mean of σ_i to be 1 to identify β. This is done by setting $\bar{\sigma} = -\frac{\tau^2}{2}$.

8 Fiebig et al. (2010) state that allowing the ASCs to scale can result in the estimates blowing up as τ and the standard errors of β can take on very large values. Additionally, they also argue that the unscaled ASC produces substantially better fit than a model where ASCs are assumed to be heterogeneous across population.

assumed that respondents' stated preference reflects their true preferences and affects the scale parameter across individuals. We decomposed the preference uncertainty ranking presented in Figure 2 into a categorical variable, with "*certain*" and "*uncertain*" levels to be estimated relative to the reference level "*Neither certain nor uncertain*".

2.4.3 Identifying Spatial Patterns

One major purpose of this study is to investigate the existence of spatial heterogeneity in people's preference for the Danda ecosystem attributes. We employ the hot spot analysis to examine the spatial patterns of the MWTP values, and this requires the characterization of individual MWTP estimates. The individual MWTP values for each ecosystem attributes were estimated by applying the Bayes theorem on the MWTP estimates following the method proposed by Train (2009) and Campbell et al. (2009).

The fundamental idea behind the hot spot analysis is to identify statistically significant local spatial clusters or patterns of high and low values (Anselin, 1995). Hot spots are essentially clusters of significantly higher events than would be expected given a random distribution of events within a defined neighborhood. Conversely, cold spots indicate a clustering of lower MWTP values. There are a number of localized statistical approaches (like Getis-Ord Gi*, local Moran's I, and local Geary's C) to identify hot spots in data. In this paper, we appeal to the Getis-Ord Gi* statistic (Getis & Ord 1992, Ord & Getis, 1995), which is one of the commonly used LISAs to investigate local hot and cold spot events. The Gi* statistic measures the extent to which spatial autocorrelation varies locally over the study area and computes a statistic for each point. The Gi* statistic is specified as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \sum_{j=1}^{n}(w_{ij})\bar{X}}{\hat{\sigma}_x\sqrt{\frac{n\sum_{j=1}^{n} {w_{ij}}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (6)$$

where, w_{ij} denotes the spatial weight matrix between observation i and j, x_j represents the value for observation j (i.e., individual specific MWTP value for attribute j), n is the total number of observations; and $\bar{X}$ and ${\hat{\sigma}_x}^2$ represents the sample mean and variance. The outputs of the G_i* are distributed as z-scores (standard deviations) and a positive (negative) large z-score indicates spatial dependence among high (low) MWTP values, which corresponds to a hot spot (cold spot).

For a statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high MWTP values (hot spot). Similarly, for a statistically significant negative z-score, the smaller the z-score is, the more intense the clustering of low MWTP values (cold spot). Specifically, the Z-scores between -1.65 and 1.65 are considered to be statistically insignificant results, while scores of $1.65 < Z < 1.96$; $1.96 < Z < 2.58$; and $Z > 2.58$ corresponds to $p<0.10$, $p<0.05$ and $p<0.01$ level of significance respectively, and indicate hot spots. Similarly, cold spots are indicated by parallel negative z-scores at identical level of significance to the hot spot scores. Furthermore, to transform the discrete hot spot information from our sample to a continuous surface over the entire population, we ran an ordinary kriging interpolation on the obtained Gi* results. Interpolation is a process of predicting unknown values over a continuous surface from a set of known observations.

2.5 Hypothesis

We are interested in testing three main hypotheses:

H1: People are less inclined to trust the municipal and the government authorities in regards to the project and funds management. This should be reflected in the public's preference for community-based management of the Danda River.

H2: The benefits provided by the Danda River are location dependent. Specifically, people in the urban town of Siddharthanagar prefer the Danda for recreational activities like boating and fishing, while people in the rural area prefer the Danda for agricultural activities like irrigation.

H3: The spatial variation and regional disparities for the ecosystem services should be evident from the presence of local hot and cold spot pockets.

2.6 Results

Table 2.2 presents the definition and the descriptive statistics of the variables used in the analysis. The choice data were analyzed using the CL, RPL, and the GMNL model, and the results are shown in Table 2.3. The RPL and the GMNL model are both estimated with the simulated maximum likelihood method using Halton draws with 1,000 replications (Sandor & Train, 2004). Column 1 lists the result of the CL model, column 2 the RPL model, and columns 3 and 4 the GMNL, one representing the model without uncertainty, and one that incorporates uncertainty, respectively. The results from all four models are broadly similar, and the sign and significance of the attributes and levels are as expected. To test the IIA property in the CL model, we ran a Hausman and McFadden test (1984) by excluding each policy option from the choice set. The Hausman and McFadden test (Table 4) firmly rejects the acceptance of IIA with the test statistic being large and statistically significant below the one percent level. To circumvent the IIA assumption, we estimated the RPL model, the findings of which are presented in column 2 of Table 2.3. The sign and significance of parameters in the RPL model is mostly consistent with the CL model. The significant standard deviation of different attributes in the RPL model suggests that preferences for most Danda ecosystem services are heterogeneous. The RPL model indeed provides a better model fit than the CL model, as evident by the lower Akaike information criterion (AIC) estimate (Table 2.3).

While the RPL model captures preference heterogeneity by allowing for random coefficients on observed attributes, it cannot account for scale heterogeneity, and this constraint can make the RPL estimates a poor approximation (Fiebig et al., 2010). We estimated the GMNL model to account for the scale heterogeneity, and the results are presented in columns 3 and 4 in Table 2.3. The GMNL model in column 3 excludes preference uncertainty, while column 4 presents the case when the self-reported uncertainty is included as an explanatory variable of the scale factor. The results from both of the

GMNL models are similar to the RPL and the CL output. The tau (τ) parameter captures the scale heterogeneity, and the positive and significant value for τ in both GMNL models suggests substantial scale heterogeneity in the data. The inclusion of uncertainty as a function of the scale parameter reduces the scale heterogeneity as τ falls from 1.77 in column 3 to 1.30 in column 4. The estimate of the parameter γ is significantly different from zero in both of the GMNL models, which suggests a GMNL-I model where the variance of residual taste heterogeneity is invariant to the scale (Fiebig et al., 2010). The estimate of the gamma parameter also confirms the existence of both the scale and taste heterogeneity.

Delving deeper into the role of uncertainty[9] in the GMNL model, the data revealed that respondents were reasonably certain about the choices they made, with an average of 4.08 (with a standard deviation of 0.96) on a scale from *Very Uncertain* (1) to *Very Certain* (5). To understand the potential source of scale, we decomposed the uncertainty score into a categorical variable with a threshold level of scores of two or less (*Uncertain*), four or more (*Certain*) and estimated it relative to the base score of three (*Neither certain nor uncertain*). The output in column 4 of Table 2.3 shows that the level of self-reported certainty for the "*Certain*" group has a significant positive effect on the scale factor, while the "*Uncertain*" group has a negative and significant effect relative to the base group. The positive (negative) effect of the certain (uncertain) group suggests that respondents' choices are more deterministic (stochastic) if they feel certain (uncertain) about their choices. This finding is in line with the result of Beck, Rose, and Hensher (2013), who found that scale

9 The uncertainty variable takes on five levels in the survey: "*Very Uncertain* (1)"; "*Somewhat Uncertain* (2)"; "*Neither Certain nor Uncertain* (3)"; "*Somewhat Certain* (4)"; and "*Very Certain* (5)".

parameter was significantly smaller for "uncertain" respondents' relative to those who made the choices with certainty.

In terms of the model fit, the GMNL models, by allowing for the heterogeneity in error scale and attribute preferences, outperform the CL and the RPL models on the basis of AIC and Bayesian information criterion (BIC) scores. The best fit amongst the two GMNL models occurs in the one that includes preference uncertainty, as evident by its lower AIC and BIC scores (Table 2.3). Consequently, the analysis henceforth is considered using the GMNL model with preference uncertainty. To investigate the welfare measures, the MWTP estimates are obtained from the GMNL model with preference uncertainty (Table 2.5).

2.7 Spatial Distribution of MWTP Estimates

To elucidate the geographical dimension of the MWTP estimates, we derived the individual specific implicit price estimates for each attribute from the estimated MWTP values. The analysis of spatial patterns to explore localized clusters first requires a global spatial association test, which we performed by using the standard univariate Moran's I statistic (Anselin, 1995). The result of the Moran's I test (Table 2.6[10]) suggests that the implicit price MWTP estimates are spatially clustered at the global level for "*River*

10 We ran the Moran's I test on the implicit price estimates of all attributes other than the "*regulatory mechanism"* attribute. The reason for the exclusion of this attribute is because the hotspot analysis is applicable only for positive values, while the WTP for regulatory mechanism is negative relative to the base group. Moreover, we focused on exploring the spatial heterogeneity in only the ecosystem attributes, and regulatory mechanism is more of a management attribute.

Quality" and "*Riverbank*" attributes, but not for "*Tree Plantation*" and "*River Monitoring*" attributes. The Moran's I test provides a formal test of the presence of global spatial autocorrelation, but does not offer any insight on spatial heterogeneity at the local level. To further explore the presence of localized patchiness in implicit price estimates, we appealed to the Getis-Ord (G_i*) statistic.

The analysis of G_i* requires a specification of the spatial unit of observations, and we defined it to be the sampled respondent households. Another crucial element in the calculation of G_i* statistic is the spatial weight matrix (W_{ij}), which captures the spatial arrangements of the units (i.e., respondent households) in the sample. We defined the spatial weight matrix based on $k=10$ nearest neighbors and a distance band of 1,500 m. We set the minimum neighborhood size to the nearest ten neighbors (i.e., k=10) since it is regarded that at least eight neighbors are needed to ensure normality of G_i* (Nelson & Boots, 2008). In terms of interpolation, the estimates of the Gi* statistic from the hot spot analysis were used as an input for kriging interpolation.

The output of the hot spot analysis and the corresponding kriging interpolation presented in figure 4A-4F suggests the presence of spatial heterogeneity for different ecosystem services. The left-hand figures (4A-4F) represent the output of the hot spot analysis while the figures on the right side are the kriging interpolation graphs. The red (green) dots are the significant hot (cold) spot areas, and they become progressively darker as the level of statistical significance increases. The white dots are the insignificant areas which displays no signs of spatial clustering for the implicit price estimates. The interpretation for the kriging interpolation (adjacent graphs to hot spot analysis) is similar. The red (green) shaded areas in the interpolation figures capture the predicted hot (cold) spot region for the entire study area, which becomes progressively darker as the z-score of the Gi* statistic increases.

2.8 Discussion and Conclusion

The objective of this paper was to evaluate the potential for a sustainable management of the Danda River and its ecosystem. The positive and significant ASC estimates across all the models in Table 2.3 indicate that on average, respondents are willing to support a new management program for Danda ecosystem improvement and wish to move away from the status quo levels. The parameter estimates of the non-monetary attributes other than "*regulatory mechanism*" are positive and mostly significant, suggesting that people derive higher utility from the ecosystem services. For the water quality attribute, respondents prefer the highest quality of river water, as indicated by "*Quality: All,*" followed by "Quality: *boating and fishing.*" Equally, respondents prefer an expansion of the riverbank, more area with trees planted along the banks, and the provision of a river monitoring and educational program. In regards to the fund and project management captured by the "*regulatory mechanism*" attribute, the findings suggest that people prefer it to be undertaken by the community. Finally, the cost coefficient is negative, which implies that an alternative is less likely to be chosen if the "*Danda management fee*" is higher. These results also confirm the internal validity of the choice experiment.

The MWTP estimates (Table 2.5), derived from the GMNL model with uncertainty, indicates that households are willing to pay, on average, NPR. 168/year ($1.63) to move away from the status quo level of ecosystem services in the Danda River. Households seem to place a rather high valuation on the Danda River for agricultural and recreational activities, a finding that has been established by other similar studies, too. The valuation for the highest quality of river water, where the Danda would be suitable for boating, fishing, and agricultural purposes, is NPR. 1,777/year ($17.25). Rai et al. (2015) found that households were willing to pay NPR. 1,548/year ($15.02) for an additional month of irrigated water in the Koshi River Basin, Nepal. The MWTP for a move to the level where water would be suitable only for boating and fishing is NPR. 776/year ($7.53). Katuwal (2012) estimated that households in the capital city of Kathmandu, Nepal valued the water from Bagmati River Basin for recreational purpose at NPR. 1,470/year ($14.27). In regards to the riverbank protection attribute, households are willing to pay NPR. 325/year ($3.15) to increase the riverbank width to 300 feet. The respondents value the planting of trees along the riverbank, which is evident by the high MWTP estimates for this attribute. The MWTP for covering 40% of riverbank area covered with trees is NPR. 895/year ($8.68), while the MWTP for 80% of coverage is NPR. 1,387 ($13.46). This result should not be surprising, since past studies have highlighted the substantial and increasing demand for tree species among the Nepalese population (Lilleso et al., 2001).

In regards to the social attributes, households prefer the implementation of a river monitoring and educational program and are willing to pay NPR. 198/year ($1.92) to instigate the program. People do not trust the national or the local government, which is apparent in the public's valuation for management undertaken by municipality as being NPR. 537/year ($5.21) less, and management by the government being NPR. 785/year ($7.61) less than if the community oversaw the full management of the Danda project. This result also sheds light on a growing movement in developing countries like Nepal where common pool resources are being effectively managed at the local level. This practice, often known as community based management, has been successfully implemented in many countries for resources like veld products (Gajuadhur, 2000), forestry (Adhikari & Lovett, 2006), and tourism (Sebele, 2010), amongst others. From a policymaking point of view, this finding suggests the need for professionals and managerial staffs in public agencies to decentralize the management of the Danda River and delegate it to the local community to enhance interest in its sustainable conservation.

Overall, the MWTP estimates for Danda ecosystem services are within the range of the cost levels provided in the CE survey. In regards to uncertainty, we found that the inclusion of preference uncertainty in the GMNL model not only improved the overall model fit, but it also increased the precision of the MWTP estimates. This result is evident in Figure 2.3, which compares the MWTP estimates obtained from the GMNL model that includes uncertainty to the GMNL model that excludes preference uncertainty. Incorporating the preference uncertainty measure in the scale parameter of the GMNL model did not change the mean MWTP estimates substantially, but it did lower the variance and produced tighter confidence bands similar to the finding of Lundhede et al. (2009). Moving on to the inspection of spatial heterogeneity, the results from the hot spot analysis and the corresponding kriging interpolation presented in Figure 2.4A-2.4F suggests that valuations of ecosystem services are indeed dissimilar at the spatial level, with localized clusters appearing in certain locations.

For instance, the Figure in 2.4A reveals statistically significant implicit price hot spots for the water quality level of "*boating, fishing and irrigation*" in the rural town of Basantapur, as well as the urban town of Siddharthangar. Alternatively, Figure 2.4B reveals that the hot spot for the level "*boating and fishing*" is more pronounced and exists solely in the urban town, indicating that households living in these urban areas are willing to pay more for "*boating and fishing*" than anywhere else. The presence of hot spots only in the urban area for the latter level suggests that people in the city possibly see the potential usage of the Danda for recreational benefits. On the other hand, the existence of hot spot pockets in the rural town in Figure 2.4A suggests that households in those areas potentially derive benefit from the Danda for agricultural purposes and thus have a high MWTP for this level. The presence of the hot and cold spot pockets is accentuated when we look at the corresponding interpolation graphs in figure 2.4A and 2.4B. This finding supports our hypothesis that people in the urban area derive benefits from recreational activities, while people in the rural location primarily value the Danda for agricultural activities.

A quick scan at the hot spot and the corresponding interpolation analyses of all the ecosystem attributes (Figure 2.4A-2.4F) indeed reveals a common pattern. There are pockets of local hot spot areas for all the ecosystem attributes in the urban town of Siddharthangar, which suggests that people in that town value improvement in Danda ecosystems. Moreover, the hot spot regions for all the ecosystem attributes in

Siddharthanagar are primarily located in the central part of that city. The central part of the city is the market area, which also houses a number of businesses and schools. Thus, this region may attract a specific kind of household, which could explain the dominance of hot spot areas in the central part of the town. Conversely, Figures 2.4A-2.4F also reveals statistically significant cold spot pockets for all the ecosystem services in the Bagaha region. These cold spot areas indicate that people in that rural community do not value Danda ecosystem services and thus have a lower MWTP than the entire study area. This finding supports the final hypothesis that preferences for the ecosystem services are spatially heterogeneous. In fact, the existence of hot spot pockets primarily in the central region of the city suggests the presence of local spatial heterogeneity and also highlights that preference for the ecosystem services are not necessarily dependent on the distance to the affected site (Danda River), as would be assumed by the continuous distance-decay method.

To understand the presence of the hot spot region in the central part of Siddharthangar, we examined the respondents' income, education levels and their support for the provision of different services in the Danda river in the hot spot region with the rest of the study area. We assumed the hot spot areas to be captured by wards 3,5,6, and 13 in Siddharthanagar, as these wards were consistently in hot spot regions for all the ecosystem attributes. It is clear from the graphs in Figure 2.5A-2.5C that households in the hot spot region in general have a higher educational level, are wealthier, and are more supportive of improving the Danda River, which would explain the existence of hot spot pockets in the central part of Siddharthanagar. The findings from the hot spot analysis can be significant to policymakers, as they provide a signal regarding the economic magnitude and spatial distribution of the local economic value of the Danda ecosystem. Consequently, policymakers can set different targets for specific areas and design programs that are consistent with public preferences.

The primary objective of this study was to assess the potential to implement a program for the sustainable conservation of the Danda River and its ecosystem. The finding that people prefer an improvement in the condition of the Danda River is indicative of local public's demand for higher quality of Danda ecosystem services to minimize the environmental and health risks. These results serve as a foundation to implement a Danda ecosystem conservation project, and our goal is to model it following the guidelines established by the "*Valle de Oro National Wildlife Refuge*" in Albuquerque, New Mexico. In fact, the *National Planning Commission*, a government body of Nepal, has granted us funds to conduct a feasibility study for the conversion of the Danda riparian system to an urban wildlife refuge site. Additionally, the results from this study have already been used as a basis to implement a pilot project called *Danda Ecological Monitoring Program* (DEMP), in Siddharthanagar, to help close the knowledge gap of the public and to promote urban ecology conservation. The primary aim of DEMP[11] is systematic collection of Danda River quality data, and will be done through a *citizen science* program using student volunteers from schools in Siddharthangar.

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11 The DEMP project is an outcome of collaboration between the New Mexico's Bosque Ecological Monitoring Program (BEMP), the University of New Mexico – Nepal Study Center (NSC), and the local partners including Pratima-Neema Memorial Foundation (PNMF) foundation, and the Lumbini Center for Sustainability (LCS) in Siddharthangar, Nepal. More information on DEMP can be found at http://pnfoundation.org.np/connecting-people-to-save-danda-river/).

An effective conservation program for the Danda River in an urban setting can certainly serve as a model example for other cities in the developing world. Moreover, the findings of our study can be useful to the policymakers of the Siddharthanagar municipality, particularly to articulate their problem, set an agenda, formulate the policy, and move to adopt it. The bottom line is that multifaceted problems like Danda conservation, with many interacting policy systems and stakeholders, will require a bottom-up cooperative approach. The scientific agency, the policy agency, and the community will have to work together to develop trust, common ground, and a sense of shared destiny. This type of social capital-building approach, if successful, can produce results that are cost effective and long lasting.

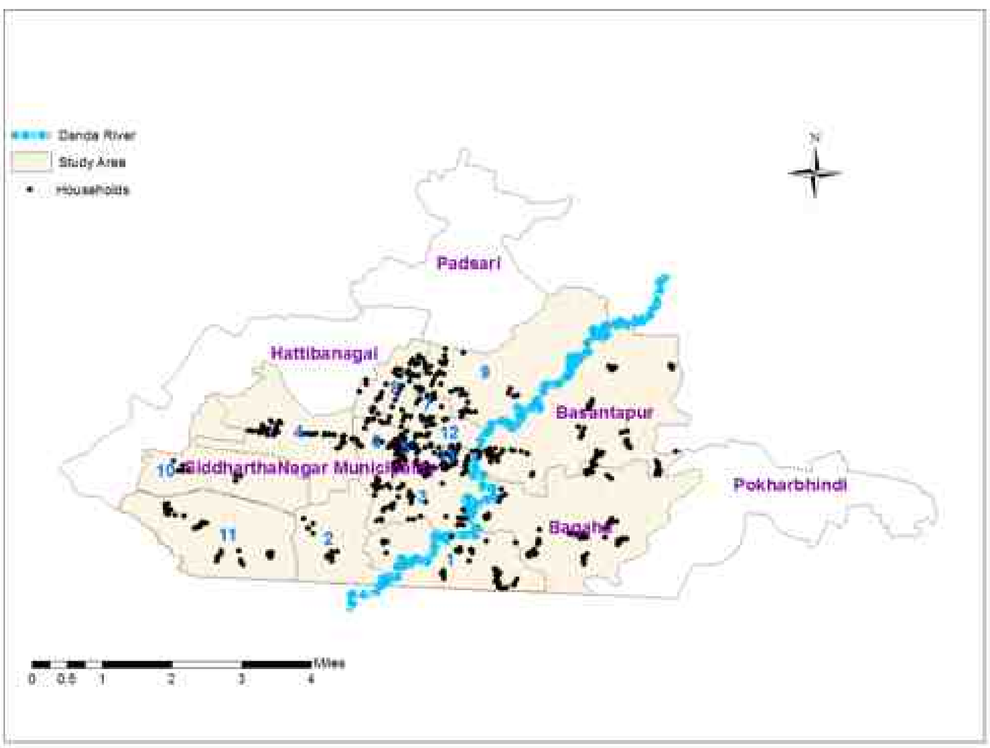
2.9 Figures and Tables

Table 2.1. Attributes and levels used in the choice experiment

River water quality	This attribute refers to the potential uses that can be acquired from Danda River.	➢ Suitable for boating only. ➢ Suitable for boating and fishing only. ➢ Suitable for boating fishing and irrigation. ➢ Not suitable for boating, fishing or irrigation*.
Riverbank protection	This attribute refers to the shoreline on both sides of the river that will be protected from any kind of urban encroachment.	➢ 50 feet* ➢ 150 feet ➢ 300 feet
Tree plantation along the riverbanks	This attribute refers to the percentage of vegetated area on each side of the river to create a natural habitat for wildlife and birds.	➢ 20%*, ➢ 40% ➢ 80%
River monitoring and educational program	This attribute refers to a regular assessment of the river water quality through chemical tests by student volunteers.	➢ Yes ➢ No*
Regulatory Mechanism	This attribute refers to the body responsible for overseeing the funds and the management of the project.	➢ Community. ➢ Government. ➢ Municipality.
Cost	An annual payment for the "*Danda river management fee*" that households would pay for the next five years.	Rs.0*, Rs.10, Rs.35, Rs.75, Rs.125, Rs.150, Rs.200, Rs.400, Rs.700, Rs.1000, Rs.1800, Rs.2500, Rs.3500.

Note: Status quo levels are marked with *

Figure 2.1. Study Area



Note: This figure shows the study area along with the respondent households used in the CE study. The urban town of Siddharthanagar lies to the left of the Danda River; while the rural town of Basantapur and Bagaha lies to the right of Danda River.
Note: The blue colored numbers in the Siddharthangar municipality are the wards. Wards are the smallest administrative units in Nepal akin to zip codes in the United States (US). Siddharthanagar municipality is divided into 13 wards.

Table 2.2: Definitions of variables

Variables	*Definitions*	*Mean*	*Standard deviation*
ASC	Alternative specific constant for management package A or B. It is a dummy variable estimated relative to the reference level of '*Management package C*: status-quo'	0.67	0.47
Quality: *All*	The highest level of river water quality suitable for '*boating, fishing and irrigation*'. It is estimated relative to the reference level of status quo, "*Not suitable for boating fishing or irrigation.*'.	0.17	0.37
Quality: *boating & fishing*	The level of river water quality that is suitable for '*boating and fishing*'. It is estimated relative to the reference level of status quo, "*Not suitable for boating fishing or irrigation.*'	0.16	0.37
Quality: *boating only*	The level of river water quality that is suitable for '*boating only*'. It is estimated relative to the reference level of status quo, "*Not suitable for boating fishing or irrigation.*'	0.15	0.36
Riverbank: 150	150 feet of shoreline on both sides of the river will be protected from urban encroachment. It is estimated relative to the reference level of status quo, "*50 feet.*'	0.223	0.42
Riverbank: 300	300 feet of shoreline on both sides of the river will be protected from urban encroachment. It is estimated relative to the reference level of status quo, "*50 feet.*'	0.19	0.39
Tree plantation: 40	40% of area on the riverbanks will be covered with vegetation. It is estimated relative to the reference level of status quo, "*20%"*	0.21	0.40
Tree plantation: 80	80% of area on the riverbanks will be covered with vegetation. It is estimated relative to the reference level of status quo, "*20%*'	0.21	0.40
River monitoring	The provision of the '*river monitoring and educational program*'. (1 = Yes, 0 = No)	0.32	0.47
Regulation: *Municipality*	The local municipal body responsible for overseeing the funds and the management of the project. It is estimated relative to the reference level of community regulation.	0.25	0.43
Regulation: *Government*	The national governmental body responsible for overseeing the funds and the management of the project. It is estimated relative to the reference level of community regulation.	0.21	0.41
Cost	Annual payment for the '*Danda river management fee'*. (NRS/ year)	568.90	965.96
Certain	Households that were either "*Very Certain*" or "*Somewhat Certain*" in their responses to the choice tasks. It is estimated relative to the reference level of "*Neither certain nor Uncertain*".	0.79	0.40
Uncertain	Households that were either "*Very Uncertain*" or "*Somewhat Uncertain*" in their responses to the choice tasks. It is estimated relative to the reference level of "*Neither certain nor Uncertain*".	0.10	0.29

Table 2.3. Preferences for Danda ecosystem services: Conditional Logit (CL), Random Parameter Logit (RPL) & Generalized Multinomial Logit (GMNL) model

Attribute	Conditional Logit	Random Parameter Logit	GMNL - No uncertainty	GMNL - Uncertainty
	(1)	(2)	(3)	(4)
Cost	-0.001***	-0.002***	-0.019**	-0.017**
	(0.0001)	(0.000)	(0.010)	(0.007)
Quality: *All*	1.895***	2.866***	33.428**	30.269**
	(0.134)	(0.414)	(18.172)	(11.896)
Quality: *boating & fishing*	0.907***	1.328***	13.697**	13.216**
	(0.118)	(0.259)	(7.867)	(5.556)
Quality: *boating only*	0.153	0.217	3.458	1.926
	(0.125)	(0.191)	(2.491)	(1.350)
Riverbank:150	0.249**	0.362*	1.904	1.505
	(0.104)	(0.197)	(1.361)	(1.559)
Riverbank:300	0.323***	0.558***	6.517**	5.533**
	(0.101)	(0.199)	(3.254)	(2.454)
Tree plantation: 40	0.963***	1.457***	16.145*	15.253**
	(0.103)	(0.238)	(9.380)	(6.300)
Tree plantation: 80	1.444***	2.389***	25.099*	23.627**
	(0.113)	(0.380)	(14.250)	(9.568)
River Monitoring	0.353***	0.485***	3.994*	3.377**
	(0.080)	(0.163)	(2.144)	(1.532)
Regulation: *Municipality*	-0.534***	-0.889***	-9.186**	-9.148**
	(0.117)	(0.238)	(4.685)	(3.761)
Regulation: *Government*	-0.906***	-1.537***	-13.725*	-13.374**
	(0.123)	(0.337)	(7.139)	(5.586)
ASC	0.551***	0.864***	1.642***	2.868**
	(0.155)	(0.243)	(0.442)	(1.236)
Standard Deviations				
Quality: *All*		1.275**	7.663**	9.289**
		(0.553)	(3.352)	(4.238)
Quality: *boating & fishing*		1.671***	12.455**	14.454**
		(0.437)	(5.987)	(6.763)
Quality: *boating only*		0.007	1.447	2.049
		(0.348)	(1.429)	(1.482)
Riverbank:150		1.354***	8.117*	8.081**
		(0.378)	(4.339)	(3.484)
Riverbank:300		0.598	6.599**	8.057**
		(0.766)	(3.309)	(4.102)
Tree plantation: 40		0.340	3.749	5.868**
		(0.752)	(2.969)	(2.684)
Tree plantation: 80		1.053**	8.427**	10.481**
		(0.490)	(4.006)	(4.900)

River monitoring		1.283***	3.937	4.674**
		(0.330)	(3.019)	(2.279)
Regulation: Municipality		0.155	0.342	1.625
		(0.937)	(1.574)	(1.309)
Regulation: Government		0.680	2.100*	2.455*
		(0.523)	(1.430)	(2.497)
ASC		1.069***	2.053***	3.518*
		(0.286)	(0.575)	(1.826)
Scale Parameters				
tau			1.771***	1.300***
			(0.235)	(0.133)
gamma			0.213***	0.673***
			(0.075)	(0.087)
Scale Parameter function				
Certain				0.460***
				(0.177)
Uncertain				-0.646**
				(0.311)
Model Statistics				
Log-likelihood	-1230	−1210	−1150	−1140
AIC	2488	2458	2352	2339
BIC	-	2585	2490	2489
N	1855	1855	1855	1855
Halton Draws	-	1000	1000	1000

*** p<0.01, ** p<.5, * p<0.1. Standard errors in parentheses. AIC: Akaike information criterion; BIC: Bayesian information criterion

Note: Dependent variable is an alternative choice. Column (1) lists the output for the CL model; Column (2) lists the output for the RPL model; Column (3) is the output for GMNL model without preference uncertainty; while column (4) is the output for GMNL model that incorporates preference uncertainty as a function of scale parameter. The RPL model is estimated by treating the cost parameter as fixed, while all other attributes are treated as random following a normal distribution. The parameters 'tau' and 'gamma' are the scale parameters for the GMNL model. For the GMNL models, the cost parameter is treated as fixed; the ASC is specified to be unscaled and random, while the other attributes are specified to be scaled and random following a normal distribution. The "Certain" and the "Uncertain" variables are the preference uncertainty measures that are modeled as a function of the scale parameter in the final GMNL model (column 4).

Table 2.4: Hausman-McFadden test for IIA

Alternative dropped	χ^2	Degree of freedom	Significance level
Management Package A	84.284	12	P<0.001
Management Package B	48.822	12	P<0.001

Table 2.6: Spatial autocorrelation in implicit price MWTP for Danda river ecosystem attributes

Implicit Price	Moran's I	z-value
Quality: *All*	0.020	3.706
Quality: *boating & fishing*	0.014	2.768
Riverbank: 300	0.012	2.406
Tree plantation: 40	0.001	0.349
Tree plantation: 80	0.001	0.875
River monitoring	-0.001	0.123

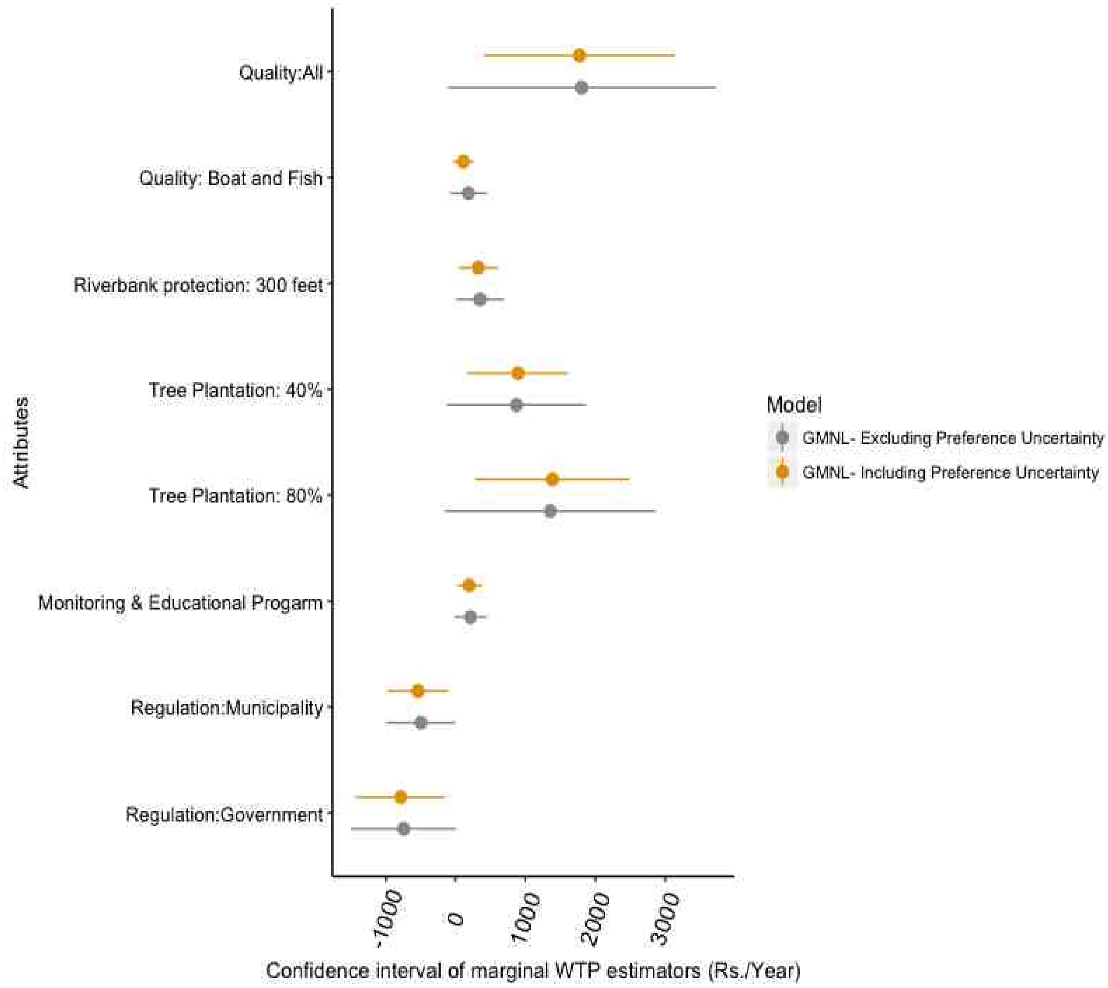
Table 2.5. Marginal Willingness to pay (MWTP) estimates for improvement in Danda ecosystem services

Attribute	**WTP**	**95% Confidence Interval (CI)**
ASC	168*** (40)	26 – 311
Quality: *All*	1,777*** (95)	408 – 3,146
Quality: *boating & fishing*	776*** (69)	136 – 1415
Riverbank: 300	325*** (71)	42 – 607
Tree Plantation: 40	895*** (64)	171 – 1,620
Tree Plantation: 80	1387*** (79)	286 – 2,488
River monitoring	198*** (45)	22 – 375
Regulation: *Municipality*	-537*** (83)	-970– -104
Regulation: *Government*	-785*** (106)	-1,428 – -142

*** p<0.01, ** p<.5, * p<0.1. Standard errors in parentheses.

Note: This table presents the marginal WTP estimates of the GMNL model with preference uncertainty i.e., Table 3, column (4). All values are in Nepali Rupees per year (NPR. /year).

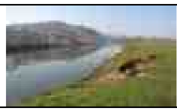
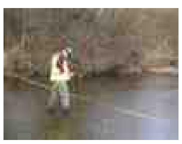
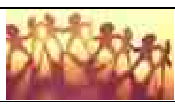
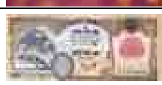
Figure 2.3. MWTP estimates and 95% confidence interval for the two GMNL models: (i) GMNL excluding preference uncertainty, and (ii) GMNL including preference uncertainty.



Note: The figure compares the marginal WTP estimates and the 95% confidence interval for the two GMNL models: GMNL with preference uncertainty and GMNL without preference uncertainty. The darker shades are the marginal WTP estimates for the GMNL model that incorporates preference uncertainty while the lighter shades are the GMNL model without uncertainty. The GMNL model with preference uncertainty has narrower confidence interval bands, however, the mean marginal WTP estimates does not vary too much between the two models.

Figure 2.2. Choice set example

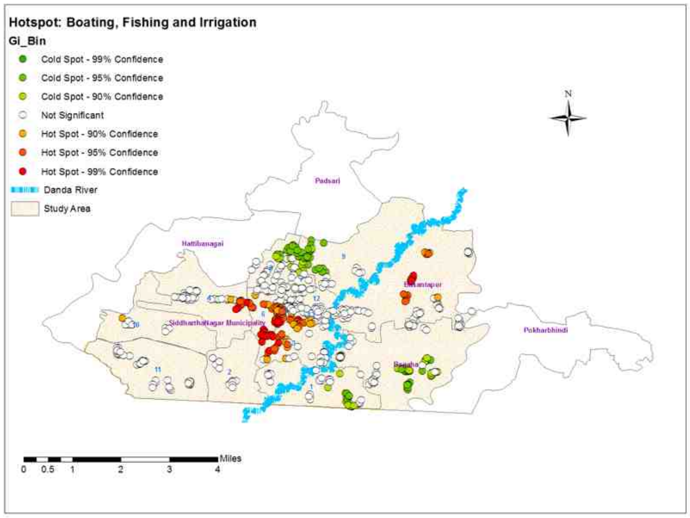
Which Danda river management package do you prefer?
You are given three different Danda ecosystem management service packages: Management Package A, Management Package B and Management Package C. Among the three packages, please choose the one that you prefer. If you are satisfied with the current situation of Danda River, you can choose Management Package C "Status Quo", which is the current situation of the river ecosystem. If none of the options exactly matches your expectations, please choose the one that you dislike the least. While choosing your answer, please consider benefits of the proposed program and your net income since the packages have different fees associated with them.

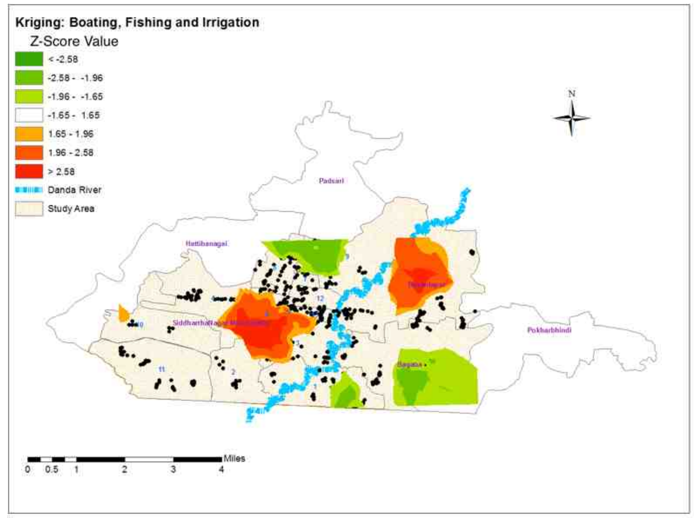
River water quality		Water will be suitable for boating and fishing.	The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation**.	The water is full of algae and it emits foul odor. Not suitable for boating, fishing or for irrigation.
River bank protection		**150 feet** on both sides	**300 feet** on both sides	**50 feet** on both sides
Tree Plantation along the riverbanks		**20%** of the bank planted with trees	**80%** of the bank will be planted with trees	Currently **20%** of the banks are planted with trees.
River monitoring and educational program		**No** monitoring and educational program	**There will be** a monitoring and educational program.	Not applicable
Regulatory mechanism		Municipality	Community	Currently not available
Management fees		Rs. 1800/year (for 5 years)	Rs. 125/year (for 5 years)	Rs. 0
Which package do you prefer (choose one only)		**I choose package A** ☐	**I choose package B** ☐	**I choose 'current situation': package C** ☐

- How certain are you of your choice?

Very uncertain	Somewhat uncertain	Neither certain nor uncertain	Somewhat certain	Very certain
1 ☐	2 ☐	3 ☐	4 ☐	5 ☐

Figure 2.4A. Hot spot analysis and Kriging Interpolation for River Quality – Boating, Fishing & Irrigation (level).





Note: This figure shows the respondent households' implicit price hot and cold spots for the attribute, river water quality – boating, fishing and irrigation (level).
(Gi z-scores, k=10 nearest neighbors, distance band = 1500m)*

Note: Hot spots are represented by the red colored points, while the cold sports are captured by the green colored points. In both the cases, the areas become progressively darker as the level of significance increases. The white dots are the statistically insignificant areas that displayed no spatial clustering of the WTP value.

99% confidence level are points with Z-scores > 2.58 or < -2.58 and p-value <0.01.
95% confidence level are points with Z-scores > 1.96 or < -1.96 and p-value <0.05.
90% confidence level are points with Z-scores > 1.65 or < -1.65 and p-value <0.10.

Note: Similar interpretation applies to the hot spot analysis of all the ecosystem attributes presented below.

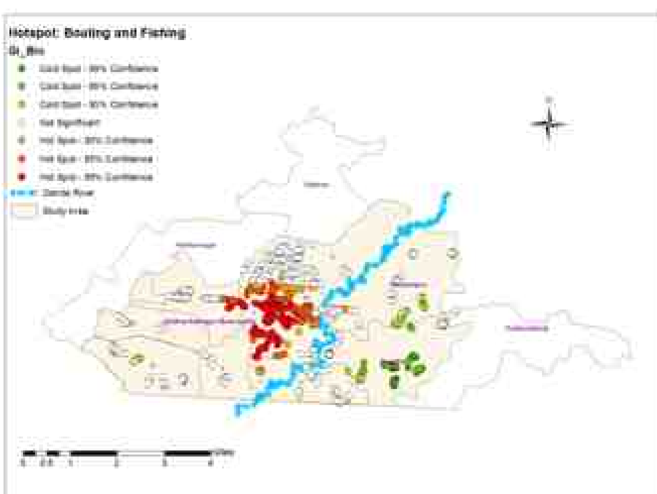
Note: This figure shows the ordinary kriging interpolation output for river water quality – boating, fishing and irrigation (level). This graph is predicted using the G_i* z-scores obtained from the hotspot analysis (left figure).

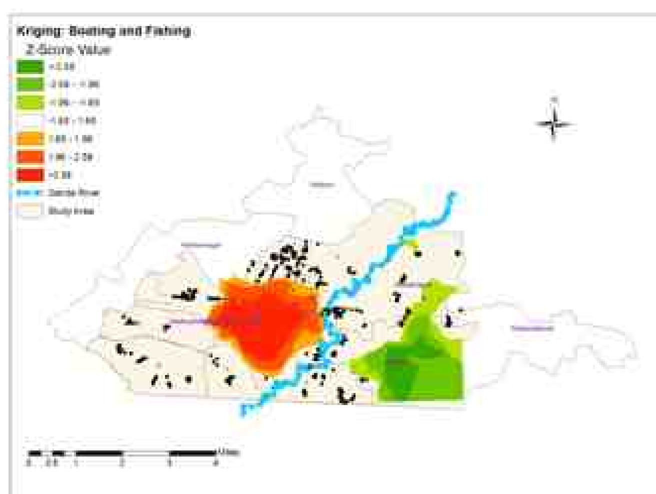
Note: Interpolated hot spot regions are represented by the red colored area, while the interpolated cold spot regions are captured by the green colored area. In both the cases, the areas become progressively darker as the level of significance increases.

99% confidence level are regions with Z-scores > 2.58 or < -2.58 and p-value <0.01.
95% confidence level are regions with Z-scores > 1.96 or < -1.96 and p-value <0.05.
90% confidence level are regions with Z-scores > 1.65 or < -1.65 and p-value <0.10.

Note: Similar interpretation applies to the interpolation graphs of all the ecosystem attributes presented below.

Figure 2.4B. Hot spot analysis and Kriging Interpolation for River Quality – Boating & Fishing (level).





Note: The figure shows the respondent households' implicit price hot and cold spots for the attribute, river water quality – boating & fishing (level).

Note: The figure shows the interpolation output for river water quality – boating & fishing (level).

Figure 2.4C. Hot spot analysis and Kriging Interpolation for River Bank Protection – 300 feet (level).

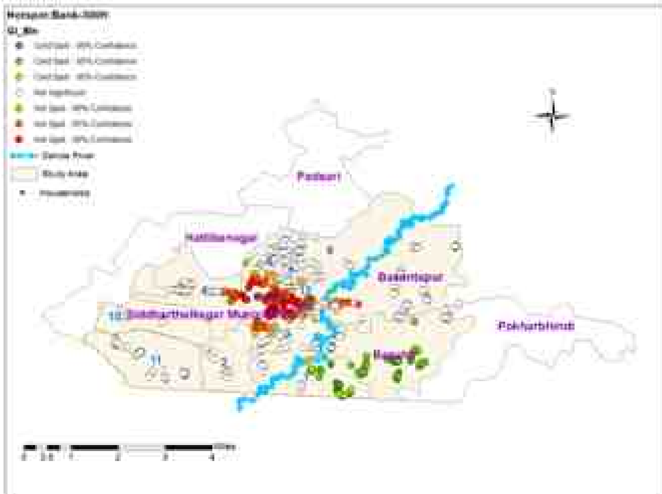
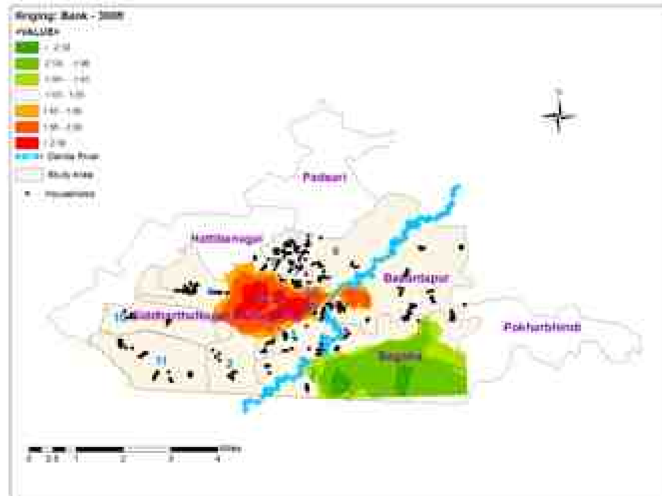
	
Note: The figure shows the respondent households' implicit price hot and cold spots for the attribute, river bank protection – 300 feet (level).	**Note:** The figure shows the interpolation output for the attribute, river bank protection – 300 feet (level).

Figure 2.4D. Hot spot analysis and Kriging Interpolation for Tree Plantation – 40% (level).

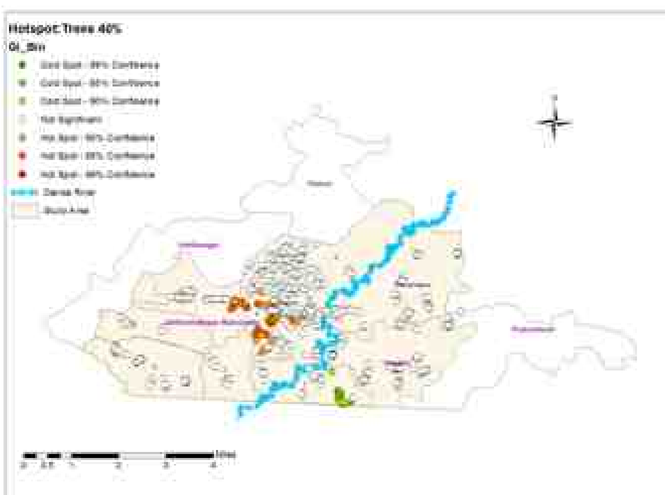
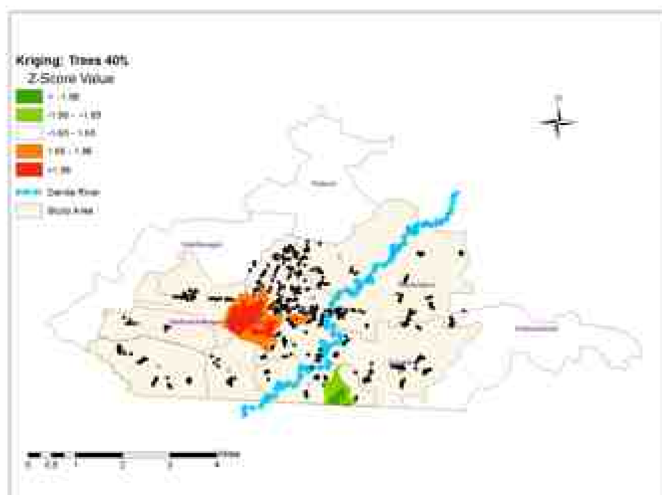
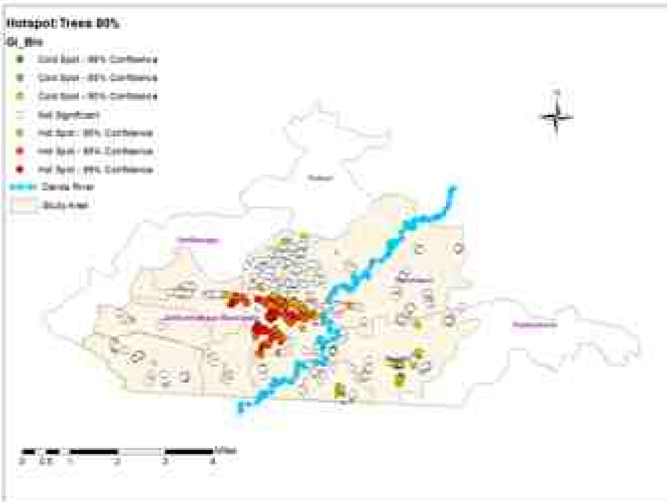
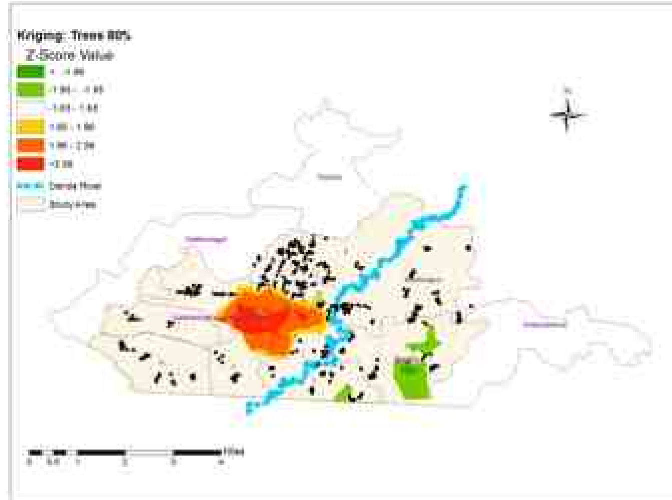
	
Note: The figure shows the respondent households' implicit price hot and cold spots for the attribute, tree plantation – 40% (level).	**Note:** The figure shows the interpolation output for the attribute, tree plantation – 40% (level).

Figure 2.4E. Hot spot analysis and Kriging Interpolation for Tree Plantation – 80%(level).

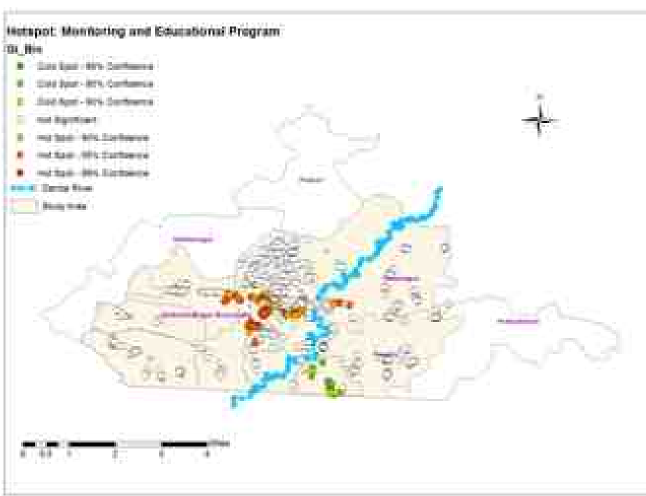


Note: The figure shows the respondent households' implicit price hot and cold spots for the attribute, tree plantation – 80% (level).

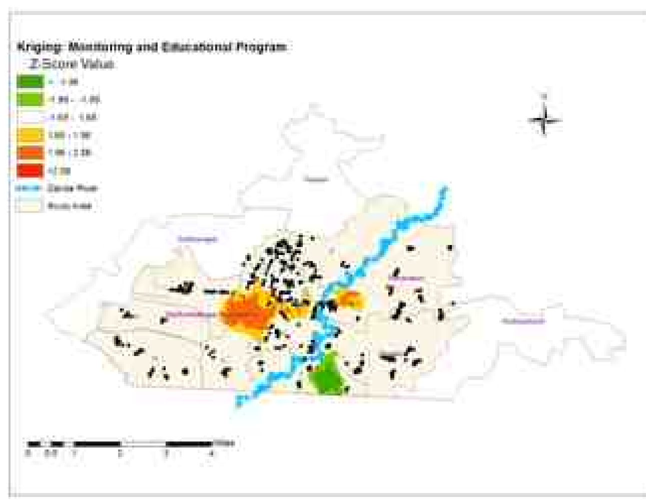


Note: The figure shows the interpolation output for the attribute, tree plantation – 80% (level).

Figure 2.4F. Hot spot analysis and Kriging Interpolation for River Monitoring & Educational Program.

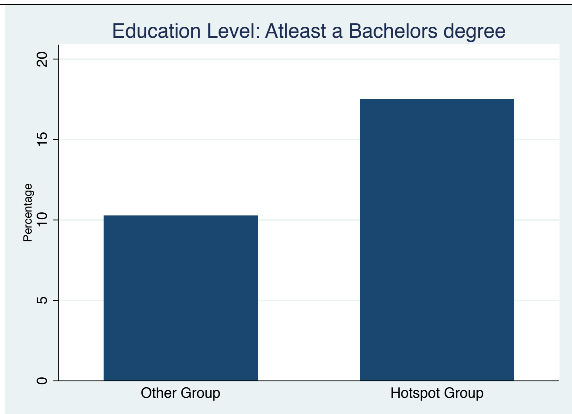


Note: The figure shows the respondent households' implicit price hot and cold spots for the attribute, river monitoring and educational program.

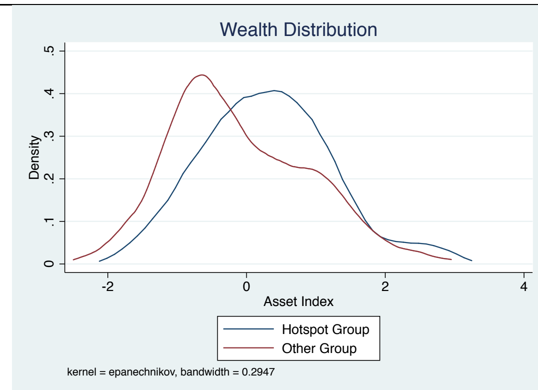


Note: The figure shows the interpolation output for the attribute, river monitoring and educational program.

Figure 2.5A. Education Level	**Figure 2.5B. Income Distribution**

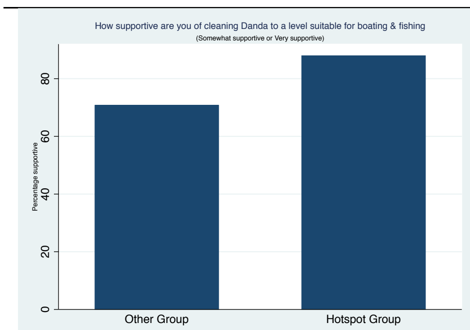


Note: This figure shows the percentage of respondents' that had at least a Bachelor's degree in the hot spot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*").

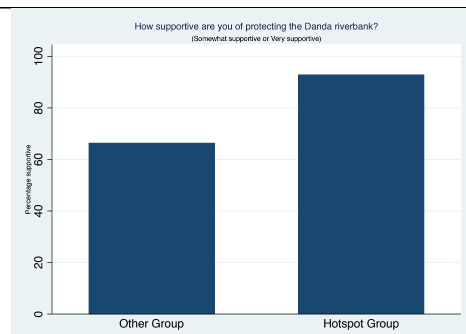


Note: This figure shows the wealth distribution of households in the hotspot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*"). We constructed an asset index as a proxy for income. The asset index was created following the methodology by Vyas and Kumaranayake, (2006).

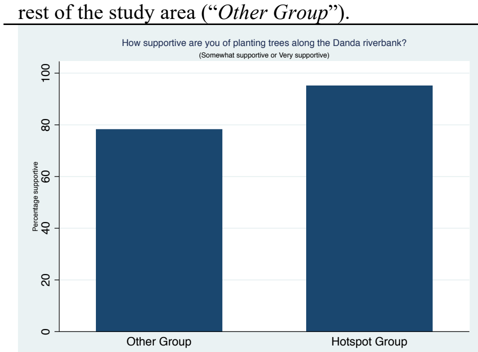
Figure 2.5C. Level of support for improvement in Danda ecosystem services



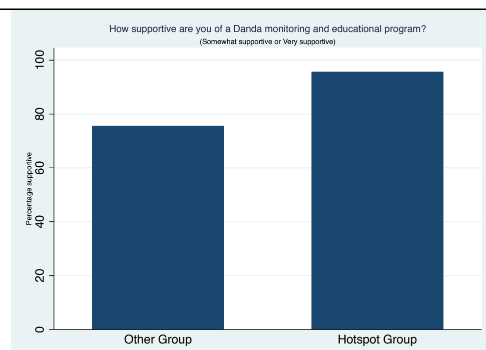
Note: This figure shows the percentage of respondents' that were at least somewhat supportive for cleaning Danda to a level suitable for "boating and fishing" in the hot spot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*").



Note: This figure shows the percentage of respondents' that were at least somewhat supportive for expanding the Danda riverbank in the hot spot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*").



Note: This figure shows the percentage of respondents' that were at least somewhat supportive for a tree plantation program in the hot spot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*").



Note: This figure shows the percentage of respondents' that were at least somewhat supportive for a river monitoring and educational program in the hot spot area ("*Hotspot Group*") v/s the rest of the study area ("*Other Group*").

Chapter 3: Water Quality Avoidance Behavior: Bridging the Gap between Perception and Reality

3.1 Introduction

One of the fundamental requirements to sustain human life is access to safe drinking water. Many developing countries face a plethora of problems in two areas: drinking water quality and availability. It is estimated that more than 1.8 billion people worldwide use a source of drinking water that is fecally contaminated, while 844 million lack access to even essential water services (WHO/UNICEF, 2017). The majority of these populations reside in the developing world, mainly in the Asian and the African countries. The children are the particularly affected groups, with more than 78% of diarrheal related annual global mortality in children attributed to poor water quality (Lucas et al., 2011). Furthermore, inadequate water supply and poor water quality can also severely impact food security, worsen hunger and malnutrition, affect livelihood choices and educational opportunities, reduce ecosystem functions, and hinder the overall economic growth (WHO/ UNICEF, 2017).

While clean and safe drinking water may not be readily available in the developing world, households' can nevertheless employ various treatment methods, some of which include boiling, filtration, or chlorinating the water to reduce the contaminants. Previous studies indicate that in-home water treatment can be one of the cheapest and most effective means of preventing waterborne illnesses like diarrhea and diarrheal diseases (Clasen et al., 2007a). Nonetheless, the widespread prevalence of water-related diseases in the developing world suggests that many households fail to engage in any water averting behaviors including in-home water treatment. A number of studies have attempted to explain households' water averting behaviors by taking into account how behaviors are initially formed. These studies largely underline the role of perceived risks in influencing water handling behaviors.

Abrahams et al. (2000) was one of the earlier papers to investigate the impact of perception on water handling behavior. They found that households in Georgia, United States that considered their tap water to be risky were more likely to engage in practices such as purchasing bottled water or using water filters than those that believed their water to be safe. There have since been other notable studies that have explored the link between perception and water averting behaviors. Um et al. (2002) found that households' adoption of averting behavior to tap water in Pusan, Korea was a result of their perceptions, even when the tap water was deemed safe to drink. (Jakus et al., 2009) investigated households in four regions of the United States and illustrate that households' risk perceptions were vital in their decision to employ in-home water treatment measures or to purchase bottled water. Nauges and Van Den Berg (2009) find evidence that a higher perceived risk increased a household's likelihood to employ treatment methods like boiling or filtration before drinking their water in Sri Lanka. Vásquez et al. (2015) explored households' perception of water quality in Leon, Nicaragua and demonstrate that households with negative perceptions of their water quality were more likely to treat their water. Other studies that have highlighted the influence of perception on water averting behaviors include those by Lloyd-Smith et al. (2018); Onjala et al. (2014); and Bontemps and Nauges, (2015).

Whereas the aforementioned studies try to explain household behaviors by highlighting the role of perception in shaping behavior, a different set of studies place significant weight on possessing information on the water quality levels as vital to changing households' behaviors. For instance, Jalan and Somanathan (2008) find that providing information on their water quality levels to households in Gurgaon, India resulted in significant changes in their water handling behavior. Households that were told their water was “dirty” (indicating a presence of fecal bacteria) were 11 percentage points more likely to make changes in their water purification, handling and/or storage behavior than households that had not been informed. In a related study, Jalan, Somanathan & Chaudhuri (2009) find that information exposure affected households demand for environmental quality. Household’s in urban India that had exposure to mass media (such as television, radio or newspaper) were more likely to adopt water averting behaviors. Katuwal et al. (2015) also confirm the findings the Jalan and Somnathan (2009) among households in Kathmandu, Nepal. They explored the factors that impacted water averting behavior of households and found that information exposure increased the likelihood of households boiling or filtering their drinking water. Luoto et al. (2011) devised a randomized field experiment in Kenya to explore the role of information provision in changing households' safe water behaviors. They find that sharing information about the local water quality level increased the likelihood of water treatment rate by 11-24% more than what was achieved by providing free water treatment products. Other noteworthy studies that highlight the role of information intervention in influencing water handling behaviors include those by Bennear et al. (2013); Hamoudi et al. (2012); and Madajewicz et al. (2007).

Thus far, the majority of the studies that have examined households' water handling behaviors have primarily converged either on exploring the influence of information dissemination on changing behaviors or examining the role of perceptions in explaining the averting behaviors. However, past studies have not really investigated averting behaviors by taking into account both, water quality information and household perceptions. This study attempts to fill that space by exploring whether the information gap that could exist due to the difference between perceived and actual water quality levels could influence the adoption of environmental risk-averting behavior. The subjective perception of the water quality level is based on the household's assessment of the safety of their water quality. The actual water quality is based on the level of *Escherichia coli* (E. coli) bacteria on the household's drinking water. We employ these two sets of data in an attempt to explore the divergence between perception and reality regarding the drinking water quality level to understand how the differences could affect a household's decision to treat their water. Incorporating subjective assessment with objective information can be vital in providing new insights into policy design, monitoring, and evaluation to approach water handling behaviors.

We draw data from 311 households in Siddharthanagar, Nepal to examine the water handling behaviors. The finding indicates that the gap between perception and reality does play a role in a household's decision to employ water treatment measures. Households' with a larger gap between perception and actual water quality levels were less likely to treat their water. On the other hand, households that had a minimal gap were more likely to adopt water treatment measures. This finding highlights the need to devise policies targeted towards minimizing the information gap to help households' make informed decisions and thereby reduce the outbreaks of water-borne diseases. Results also suggest the water source, the taste of the water, and education level of the households also affected the water handling behaviors.

3.2 Country Background, Study Site, and Survey Data Collection Approach

Nepal is a tiny developing country sandwiched between India and China. The widespread water quality concerns in the developing world are no exceptions to Nepal. The availability of water is not as much of a significant concern since more than 88% of the households had access to a water source in 2015 (WHO /UNICEF, 2017). However, improved access does not necessarily reduce the risk of microbiological contamination in the drinking water, thus, water quality remains an issue. In fact, only about 27% of the population has access to safely managed water supplies free from contamination (WHO /UNICEF, 2017). This issue has contributed to major health outbreaks in Nepal ranging from infant and child mortality rates to high incidences of fecal-orally transmitted diseases. Water quality concerns in the country are further exacerbated due to the rapid and haphazard urbanization that has resulted in high population density in the major urban areas.

Almost 47% of Nepal's total population lives in the lowlands in the south, known as the Terai region. Water quality issues in the Terai region primarily stems from the presence of contaminants like coliform, nitrate, iron, ammonia, and arsenic (ADB, 2011). This paper explores the water handling behaviors of the households using a sample from a primary survey carried out in 2016 on Rupandehi district in the Terai region of Nepal. The survey was conducted in the urban city of Siddharthanagar, and its two adjacent rural settlements, Basantapur and Bagaha. The Siddharthanagar municipality is considered as a major trading city in Nepal and is located on the border of Nepal and India about 170 miles west of the capital city of Kathmandu. The city is promptly expanding with a total population of 163,483 (CBS 2011). The piped water supply system in the region is administered by a public utility, the Nepal Water Supply Corporation (NWSC), but it serves only about 30% of the existing population (ADB, 2011). The primary source of water supply in the region is groundwater sources obtained through water pumps; however, the risk factor of bacteriological contamination, particularly in shallow groundwater can be pretty high (ADB, 2011).

The household survey was conducted between May-July 2016, and the data were collected through in-person interviews. The survey was carried out to explore the environmental and health problems in urban Nepal. The survey protocol included expert interviews with water management officials, focus-group discussions, debriefing, pilot survey and the final survey. The households were selected using stratified random sampling and they were interviewed to assess their knowledge, attitudes, and practices regarding water use and hygiene behaviors in the urban ecosystem. The majority of the sampled households (84%) belonged to the urban city of Siddharthanagar, while the remaining 16% comprised of households from Basantapur and Bagaha Village Development Committee (VDC) (Table 3.1).

In addition to the survey, a water quality test was carried out to measure the presence of E. coli bacteria on the household's drinking water. This test was carried out on 311 households[12]. The test for the E. coli bacteria was conducted using a single use disposable testing kit developed by the *LaMotte Company*[13]. A water sample of 10 ml was collected from each household, and the water sample was taken to a laboratory for testing. The collected water samples were then placed in an incubator at a temperature of (45^0 C) for 48 hours to obtain the result. The presence (absence) of the E. coli bacteria was confirmed by examining the sample through an ultraviolet (UV) light, which glows (does not glow) in the presence (absence) of the bacteria. A figure of the test procedure is presented in Figure 3.4.

3.3 Existing Water Uses, Water Quality Perceptions, and Gap

In-home treatment of drinking water is an effective mitigation strategy to combat water induced health problems; however, a preliminary glance of the descriptive statistics suggests that the majority of the households' in our sample do not employ any water

[12] The overall survey was completed by 637 households, representing an effective response rate of about 90%. Of the total household sample, we conducted the E. coli test only on 311 randomly selected households. This was because purchasing a testing kit for all the households was out of our budget.

[13] More information on the E. coli testing kit can be found here: http://www.lamotte.com/en/drinking-water/microbiological-testing/4-3616-uv.html

treatment measures (Table 3.1). The dichotomous indicator TREAT captures the variable that measures the averting behavior. This variable takes a value of 1 if a household employs any treatment measures[14], and 0 if a household did not treat their water. Only one-third (34%) of the households in our sample used some kind of treatment measures for their drinking water. Among the households that treat their water, the primary method used by 21% was boiling (BOIL), with filtering (FILTER) being a distant second alternative used by only 6% of the households. The remaining 7% of the sample employed other treatment methods including chlorination, using solar disinfection, or the use of euro guard (a type of water softener and purifier commonly used in South Asia).

The majority of the households received their water from one of four different sources: (i) About 33% of the households had connection to private taps (PRIVATE_WATER); (ii) Almost 16% used public taps (PUBLIC_TAP); (iii) 38% of the households used shallow private tube-well (TUBEWELL), and (iv) 11% of the households use groundwater boring (BORING) as their primary water source. The difference between the two groundwater sources, shallow tube-well and boring, comes down to the depth of the water source. While both the sources come from below the ground; boring water sources in the area are considered to be those that are extracted from 65 feet depth below the ground. These deep aquifers are generally considered to be safe from pollutants but are expensive to install, and hence may only be available to the wealthier households in general.

[14] The households that treated their water were asked to choose their primary methods of treatment and were given the option between boiling, adding chlorine, filtering, using euro-guard, solar disinfection or straining through a cloth.

To explore the water quality information gap among the households', we relied on two sources of data: *water quality perception*, and the *actual water quality data*. The water quality perceptions (QUALITY_PERCEPTION) were based on the households' subjective rating of their water quality levels. The households were asked to rate[15] the riskiness of their drinking water before treatment in terms of whether they thought their water contained any harmful bacterial contaminants. The households were given an option between (1) no risk, (2) little risk, (3) some risk, and (4) serious risk. The majority of the households perceived their water quality to be quite safe, as presented in Figure 1. The skewed distribution of the water quality perception (i.e., the majority of the households' perceiving their water quality to be safe) has been found in other studies too. Vásquez and Trudeau (2011) find that less than 23% of the households in Matiguas, Nicaragua rated their water quality as "bad" or "very bad", while Katuwal and Bohara (2011) state that only 10.5% of the households in Kathmandu, Nepal had a poor opinion of their water quality levels.

The data for the actual water quality level was based on the E. coli tests conducted on the households' drinking water. One point to note is that the E. coli testing kits used on the households were only designed to indicate the presence or an absence of the bacteria, and they did not reveal the total count of the E. coli bacteria in the water. It is generally considered that water should contain less than 1 colony forming unit (CFU) per 100 milliliters of E. coli bacteria to be suitable for drinking (WHO, 2004). While the E. coli

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[15] We decided to use an ordinal measure of risk perception rather than a probabilistic rating since the former technique was much easier for the households to comprehend during the pre-testing phase of the survey.

test used in our study does not specify the count of the bacteria, the presence of even a miniscule amount of E. coli bacteria is still an indication that the water might contain other kinds of bacteria, viruses or protozoa that can make a person sick (WHO, 2004).

Since the water supply in Nepal is not reliable, many households tend to store their water in a storage vessel (like clay pots, buckets, barrels, etc.) for later use. The water sample to conduct the E. coli test was thus collected from the container where the households stored their water before treatment rather than from the point source. Although we did not take the water sample for the E. coli testing from the point source, previous studies have suggested that E. coli contamination is equally likely to occur from water storage containers (particularly earthenware jars) (Gilman and Skillicorn, 1985; VanDerslice and Briscoe, 1993). The E. coli results presented in Figure 3.2 indicates that almost 35% of the households' drinking water were contaminated with the E. coli bacteria.

Table 3.2 presents the conditional frequency table between the households' perception of their water quality and the objective water quality level. Among households that considered their water to be free from risk, almost 33% of the household's water was contaminated with the E. coli bacteria. The percentage of households whose water were contaminated with E. coli slightly increases among households that considered their water quality to be risky. For instance, the drinking water of about 41% of the households that considered their water to be somewhat risky, and 40% of those that considered their water to be seriously risky were contaminated with the E. coli bacteria. While the pattern in Table

3.4 indicates that perceived risk increases with the presence of E. coli, the relationship is not significant, and more analysis is required to get an accurate picture.

Based on the households' subjective and the objective water quality level, a variable to measure the divergence between perception and the actual water quality level was created (*INFORMATION_GAP*). The *INFORMATION_GAP* variable is a categorical variable that consists of four categories as presented in Figure 3.3. The first category captures the households that considered their water source to be free from risk (QUALITY_PERCEPTION = 1), but the water quality test suggested a presence of the E. coli bacteria (ECOLI_WATER=1). We call this group of households *"Group 1: Ignorant and Optimist"* since this group perceived their water quality to be better than what it actually was. Almost 18% of the sample fall into the first category. The second category represents the households that perceived their water to be free from risk (QUALITY_PERCEPTION = 1), and the scientific test also confirmed good quality water in the form of an absence of E. coli bacteria (ECOLI_WATER=0). While this group had similar perceptions to the former group, their perceptions also matched the reality, unlike the "*Group 1: Ignorant and Optimist*" group. We name these group of households the *"Group 2: Aware and Optimist"* group, and almost 35% of the households belong to this group.

The third category comprises of households that considered their water to be risky (QUALITY_PERCEPTION = 2, 3 or 4), and the scientific test also confirmed bad water quality in the form of a presence of the E. coli bacteria (ECOLI_WATER=1). We call these households *"Group 3: Aware and Pessimist"* which consist of 16% of the household sample. The final group in the *INFORMATION_GAP* variable are those households that considered their water to be risky (QUALITY_PERCEPTION = 2, 3 or 4), but the scientific test did not reveal any presence of E. coli bacteria (ECOLI_WATER = 0). This group of households are opposite to the first group in that they had a worse perception of their water quality level, but the E. coli test indicated good quality water. We call this group of households *"Group 4: Ignorant and Pessimist"* which comprised of 30% of the total sample. In this study, the households whose perception matched the actual water quality level (e.g., "*Group 2: Aware and Optimist*", and "*Group 3: Aware and Pessimist*" groups) are considered to be the ones with minimal information gaps.

Table 3.3 presents the conditional frequency table between the four household groups and their treatment behavior. It is evident from the table 5 that only 22.43% of the households in the "*Group 1: Ignorant and Optimist*" and 9.35% of the households in "*Group 4: Ignorant and Pessimist"* group treat their water. Among the households with minimal gap, the treatment behavior is somewhat different. Almost 42.06% of the households in *"Group 2: Aware and Optimist*", and 26.17% in "Group 3: Aware and Pessimist" treat their water. The Pearson χ^2 value of 21.7834 suggests that the observed differences between the household groups and their treatment behaviors are significantly different. This table provides a preliminary evidence that the behavioral responses of the households with divergent gap (*Group 1 and Group 4*) are contradictory to the households with minimal gap (*Group 2 and Group 3*).

3.3.1 Profile Sample of Households

Table 3.1 presents the socioeconomic profile of an average household that responded to the survey. The variable *WATSATIS* is a dichotomous indicator that takes a value of 1 if the households were satisfied with the taste of their drinking water. The statistic suggests that almost 89% of the households were content with the taste of their water. The variable *COLLEGE* captures the education level of the respondents, and only about 18% of the respondents had obtained at least some college level education. We asked our sample if any member of the household had contracted a waterborne disease (Diarrhea, Dysentery, Jaundice or Cholera) in the last 30 days, and about 45% of the households had a family member that had been sick (*SICK*) with a water-borne disease. Almost 43% of the households had children that were less than five years old (*CHILD*), while 14% of the respondent lived in a rental place (*RENTAL*). The variable *ETHNICITY* captures whether a household belonged to either the Brahmin or the Chhetri community. The Nepalese society is divided into a caste system, and the groups mentioned above are considered to belong to the upper -caste. Almost 43% of our respondents belonged to one of these communities. Figure (1.10) presents the wealth distribution of households based on the possession of different durable goods. The asset index was created using the principal component analysis (PCA) following a methodology similar to Vyas and Kumaranayake, (2006). The durable goods considered were whether a household possessed assets like radio, television, telephone, fan, air conditioner, bicycle, motorcycle, car, refrigerator, washing machine, and computer. The asset index was created using the principle component analysis.

To capture the socio-economic position of the household, an asset index (*WEALTH*) was constructed using information on the households' possession of durable[16] goods. The predicted asset index was then divided into three different quartiles for the analysis. The survey also presented simple factual questions to the households to measure their knowledge on science, and these factual data were used to create the knowledge index[17], captured by the variable *SCIKNOW*. The index ranged from 0 to 1, and a higher value for the variable indicates that the households correctly answered all the factual questions presented to them, i.e., these households possessed a greater scientific knowledge.

3.4 Analytical Framework

The primary interest of this study is to understand how differences in the subjective and objective value on water quality levels can affect a household's water treatment behavior. Thus, the hypothesis stems from the households' misaligned views on their subjective and actual water quality levels. We argue that the households with a larger information gap between the subjective perception and actual water quality levels are less

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[16] The durable goods considered were whether a household possessed assets like radio, television, telephone, fan, air conditioner, bicycle, motorcycle, car, refrigerator, washing machine, and computer. The asset index was created using the principle component analysis.

[17] The knowledge index was created based on these questions presented to each household: (i) Does fertilizer and pesticide cause algae to grow and ultimately destroy water plants? (ii) Does polluted water carry any diseases?; Which disease between diabetes, diarrhea, and cancer can be caused by ingestion of polluted water?; and (iv) whether a household had ever heard of the E. coli bacteria.

likely to treat their water relative to households that have minimal gaps. Furthermore, if divergence does play a role in water averting behavior, then it should be expected that households with a similar level of divergence should not be too different from each other in terms of their water handling behavior.

The theoretical framework to explore the averting behavior follows a variant of the traditional household production function approach that has been employed to analyze various averting behaviors (e.g., Bartik, 1988; Larson and Gnedenko, 1999; Um et al., 2002). Since similar theoretical models have been presented elsewhere, the discussion of the theoretical framework is kept to a minimum. We assume that households' water averting behavior is driven by the information gap that arises through the differences in two factors: the perceived riskiness of the water, and the actual water quality level. Based on these differences, we assume that households procure water by adopting strategies to avoid the adverse effects of drinking unsafe water. For instance, households could employ in-home treatment (e.g., boiling, filtering or chlorinating), or they could also purchase water from outside sources. The averting measures are beyond the scope of this paper, and the focus here is on the role of information gap on any averting behavior (i.e., whether a household treats their water or not).

The household production function for an improved (intended) quality of water ($\boldsymbol{Q}$) can be stated as:

$$Q = f(T, G) \tag{7}$$

Where the intended quality of water depends on two variables: ***T*** is the averting behavior, and ***G*** is the gap between the objective water quality and the perceived water quality level. The function *f* is assumed to be increasing in **T** and decreasing in ***G*** (i.e., $f_t > 0$, and $f_G < 0$). The minimum expenditure on averting behavior required to reach a water quality level of ***Q*** given the information gap of ***G*** can then be stated as:

$$E(p, Q, G) \equiv min_T \; p * T \; s.t. Q = f(T, G) \tag{8}$$

Where ***p*** is the price of the averting behavior. A household is assumed to maximize their utility by choosing the optimal quality of water ***Q****, and composite good ***Z*** subject to their budget constraint, which can be shown as:

$$\underbrace{\max}_{Q,Z} U(Q^*, Z;\ \beta) \tag{9}$$

$$s.t.$$

$$E(p, Q^*, G) + Z \leq I$$

A household cannot spend more than its income which is denoted by ***I*** in equation 3. The variable β captures the characteristics of a household. It can be shown that there is an optimal averting measure (***T****) which depends on the price of the avoidance behavior (***P***), the households' information gap (***G***), the households' level of income (***I***), the characteristics of the household (***β***), and the optimal level of water quality (***Q****):

$$T^* = T^e(p, G, Q^*(p, G, I, \beta) \quad (10)$$

The empirical estimation to equation (4) can be conducted using various methods. In our analysis, the optimal treatment behavior takes a discrete form which can be modeled as a probit (or logit) relationship.

3.5 Empirical Analysis

The household's water averting behavior is investigated using the probit framework. Since the primary objective of the study is to investigate whether the behavioral differences in water handling behavior can be attributed solely to the perception of the water quality; to the objective water quality level; or the divergence between the two, the probit model takes the following expression:

$$y_i^* = E_i\gamma + R_i\delta + (E_i * R_i)\theta_i + X_i\beta_i + \varepsilon_i \quad (11)$$

Where the latent variable y_i^* captures the households' decision to treat their water, the vector E_i is a dichotomous variable that captures the household's objective water quality level (*ECOLI_WATER*), R_i is also a dichotomous variable that captures the household's risk perception of their drinking water quality[18], and $(E_i * R_i)$ captures the divergence between the subjective and objective water quality[19]. Since both the variables E_i and R_i are considered to be dichotomous, the variable $(E_i * R_i)$ is essentially

[18] R_i is assumed to take a value of 1 of *QUALITY_PERCEPTION* = 2, 3 or 4 and a value of 0 if *QUALITY_PERCEPTION* = 1.

the *INFORMATION_GAP* variable with four household groups as discussed in Section 3.3. The vector X_i captures the variables associated with the household's water characteristics (e.g., the source of drinking water, the taste of the drinking water) and socio-demographic characteristics (e.g., ethnicity, income, knowledge, children, homeowners, location). γ, δ, θ_i and β_i are the parameters to be estimated, and ε_i is the error term that captures the unobserved determinants of treatment behavior that is assumed to be normally distributed with mean 0 and variance 1. The latent variable ${y_i}^*$ drives the observed outcome of the household employing water treatment, y_i through the following rule:

$$\begin{cases} y_i = 1 \; if \; {y_i}^* > 0 \\ y_i = 0 \; if \; {y_i}^* \leq 0 \end{cases}$$

Since the survey data was collected through clustered stratified sampling, a robust regression approach was applied by accounting for heteroskedasticity (i.e., cluster-specific variance). Before estimating the probit model presented in Equation (5), we started with a basic probit model. Table 3.4 presents the output of the probit estimation where the first panel presents the outcome on the treatment behavior for the different groups of households based only on their information gap level. The second panel presents the result of the treatment behavior by looking at the households' perception of their water quality and the level of E. Coli in their drinking water.

The result in the first panel of Table 3.4 suggests that households with wider gap (*Group 1: Ignorant and Optimist* and *Group 4: Ignorant and Pessimist*) were less likely to treat their water relative to the minimal gap household (*Group 2: Aware and Optimist*). On the other hand, the behavioral difference between the households with minimal gap (*Group 2: Aware and Optimist* and *Group 3: Aware and Pessimist*) was insignificant. The second panel in Table 3.4 provides evidence that households that perceive their water quality to be risky were more likely to treat their water. While the result from the first and second panel in table 3.4 provides preliminary evidence that risk perception and information gap both plays a role in shaping a household's water averting behavior, it is not clear whether the effect arises because of perceived risk or objective water quality, or the divergence between them. To clarify this ambiguity, the probit model in the third panel of Table 3.4 presents the finding when the perceived water quality and the objective water quality were interacted with each other.

Table 3.5 presents the estimate of the probit model by including various sets of control variables. The first panel in Table 3.5 lists the output by controlling for water characteristics, the second panel adds knowledge and health variables while the third panel adds additional control variables for household and locational characteristics. Table 3.7 presents the output of the probit model which compares the treatment behavior of households that use any mode of treatment (*TREAT*) to households that primarily boiled their water (*BOIL*), and for those where filtration was the primary means of treatment (*FILTER*). The results in Table 3.4, 3.5 and 3.7 are quite revealing about the association between a household's water treatment behavior and the information gap, once other factors have been controlled for. The general findings suggest that the behavioral difference between the household groups with minimal gap, '*Group 2: Aware and Optimist*' and '*Group 3: Aware and Pessimist*" are not statistically different. On the other hand, household groups with wider gap were less likely to treat their water relative to the households with minimal gap. The results do not change when even when we separate the treatment modes to *BOIL* and *FILTER*.

3.6 Discussion

The result of the probit models in Table 3.4, 3.5 and 3.7 are similar with the signs of the statistically significant coefficients in the expected directions. Overall the findings indicate that the water handling behavior of households with minimal gap are dissimilar to those that have a wider gap between perception and objective quality. The output in Table 3.4 presents the water handling behavior of the households by excluding the control variables. The first panel in Table 3.4 suggests that households with wider gaps (Group 1 and Group 4) were less likely to treat their water relative to household with minimal gap (Group 2), and the second panel suggests that household that perceived their water to be risky were more likely to treat their water. However, a better picture of the water averting behavior is evident from the third panel in Table 3.4 which shows the overall effect of perception and objective water quality on the likelihood of employing water treatment measures.

The result in the third panel in Table 3.4 indicates that the objective water quality level (i.e., presence or absence of E. Coli) does not significantly affect the water handling behavior of households by itself. Conversely, households that considered their water risky were more likely to treat their water, which is consistent with the literature on water handling behavior (Abrahams et al., 2000); Jakus et al., 2009; Vásquez et al., 2015).

However, the noteworthy finding from the third panel in Table 3.4 was with regards to the interacted variables. Results suggest that the gap between perception and reality may also be equally important in altering households' water handling behaviors. For instance, households that belong to Group 1 and Group 2 are those groups that both considered their water quality to be free from risk[20]. Group 2 was correct in their assessment since the actual water quality also turned out to be risk-free, while the water quality of Group 1 was contaminated. Likewise, households that belonged to Group 3 and Group 4 both considered their water to be risky. In this scenario as well, the water quality of households in Group 3 was actually risky, while the water quality of households in Group 4 did not contain any E. Coli bacteria.

If perception alone was the determining factor for water treatment behavior, then the water averting behavior of households that belong to Group 1 and those that belong to Group 2 should be similar since they both considered their water quality to be safe. A parallel argument applies to the households that belonged to Group 3 and the households in Group 4, where both groups of households considered their water to be risky. However, the result indicates that in either of the cases, households with minimal gaps were more likely to treat their water than households with wider gap. In the first scenario, households with a wider gap Group 1 were less likely to treat their water than households in Group 2. Similarly, households that belonged to the minimal gap Group 3 were more likely to treat their water relative to households in Group 4. This finding provides evidence that an

[20] See Table 3.1. By definition, Group 1 are those groups that thought their water was risk-free, but the E. coli test indicated presence of the bacteria. Similarly, Group 2 are those households that considered their water to be risk-free and the E. coli test also did not reveal any contaminants.

additional element driving the water averting behavior could be the gap between the subjective level and actual quality.

It should be noted that households in Group 3 are those that considered their water to be risky and it actually was risky. The finding that this group of households were more likely to treat their water seems plausible since these households possessed accurate information on their water quality level. On the other hand, households in Group 2 are those that considered their water to be safe and it actually was safe. Yet, this group of households were also more likely to treat their water than the households in Group 1 or Group 4. The higher likelihood of this group employing water treatment measures could be because informed households may make more cautious decisions. It is also possible that this informed group understands that water-related health problems can occur through a myriad of contaminants, and not only through the presence of the E. coli bacteria. Thus, this informed group was more likely to treat their water to protect from other contaminants, even though they knew their water did not contain any E. coli bacteria.

Moving away from the comparison of household groups with similar perception, the result is analogous even for household groups that shared the objective water quality levels. Households that belonged to Group 4 and Group 2 both were tested negative for the presence of E.Coli in their drinking water; and households in Group 3 and Group 1were tested positive for the presence of E.Coli present in their water. The result still suggests that households with minimal gaps Group 2 and Group 3 were more likely to treat their water than their counterparts. The general result across the different household groups suggest that it is not the subjective perception or the objective water quality alone that drives behavior, but a combination of the two. Finally, the results in panel 3 of Table 3.4 suggests that households with minimal gap Group 2 and Group 3 did not have significant behavioral differences in their water handling behavior. Likewise, households with wider gap Group 1 and Group 4 also did not have significant differences in their behavior.

The latter two finding suggests that households with minimal gap behave in a similar manner to each other, and the behavior of households with wider gap also are alike (i.e., either of these groups were not likely to treat their water more or less relative to the other group). This result is instinctive, and it indicates that the lack of behavioral difference between either of these groups is because the former two groups both possessed accurate information on their water quality levels, while the latter two groups both possessed false information. Hence, neither of those set of groups were different from each other in terms of their water averting behavior.

Table 3.5 presents the probit model with control variables, and the result does not change after adding different set of controls. The first panel in Table 3.5 lists the probit outcome when including the variables associated with the drinking water characteristics, the second panel has additional controls to include educational and health background of the households, and the third panel presents the result of the full probit model with demographic and locational characteristics as well. Table 3.6 presents the marginal effects from the full probit model. The results across all three probit models still supports the finding in table 4 and suggests that households with wider gaps were less likely to treat their water than households with minimal gap. The marginal effect of the probit model in Table 3.6 suggests that households that considered their water to be risky were 6 percentage points more likely to treat their water, while the relationship between the level of E.Coli and treatment behavior was not significant. Relative to households that belonged to Group 2 (minimal gap), households in Group 4 were 12 percentage points less likely to treat their water, while those in Group 1 were 25 percentage points less likely to treat their water. Similarly, households in Group 2 (minimal gap) were 26 percentage points more likely to treat their water relative to households in Group 4, and 38 percentage points more likely compared to households in Group 1.

The other general findings from the marginal effects of the probit model in Table 3.6 suggests that households that received their water through private taps were 9 percentage points more likely to treat their water than those with public water source. The coefficient for the households using groundwater sources like tube-well and boring suggested they were less likely to treat their water although the variables itself were not significant. The taste of the drinking water also affected households' decision to employ water treatment with the result suggesting that households satisfied with the taste of their drinking water 15 percentage points less likely to treat their water. This finding implies that the aesthetic attribute could also influence a households' behavior. Nauges and Van Den Berg (2009) also found that households' in Sri Lanka that were content with the taste of their drinking water were less likely to treat it. The variables associated with the households' knowledge and health status reveals that households that possessed at least some college education were about 16 percentage points more likely to treat their water.

This finding insinuates that literate households are better able to comprehend the potential risks of drinking untreated water, and thus, are more likely to treat their water. Education has been found to increase the demand for environmental quality in several water averting behavior studies (Jalan, Somanathan & Chaudhuri, 2009; Katuwal et al., 2015 etc.).

The variable associated with the household wealth suggests that the income was not a significant determinant of treatment behavior. Previous studies have found a rather ambiguous effect of wealth on water averting behaviors. For instance, Francisco (2014), and Vásquez et al. (2015) both found the impact of income on households' water treatment behavior to be insignificant. While household wealth was not a significant determinant of averting behavior, the result suggests that households that belonged to the Brahmin or Chhetri communities were about 9 percentage point more likely to engage in water averting behavior. These ethnic groups are considered as upper-caste groups and are traditionally assumed to practice purity rituals in the Nepalese society, thus the result is not surprising. Katuwal and Bohara (2011) also found that households that belonged to Brahmin or Chhetri communities were more likely to boil or filter their water in Kathmandu, Nepal. The finding in Table 3.6 also indicates that households that had children were about 6 percentage points more likely to treat their water. Finally, the result suggests that rental households were about 15 percentage points less likely to treat their water compared to homeowners. (Vásquez, 2012) also found that rental households in Nicaragua were less likely to expend on water storage devices.

To confirm the consistency of our result, we carried out the probit estimation of water averting behavior by separating the households into those that primarily boiled their water, and those that used filtration as the primary treatment method. The results presented in Table 3.7 do not change significantly even the when modes of treatment are separated. The findings in Table 3.7 still suggests that the households with wider gaps were less likely to treat their water relative to households that had minimal gaps. Thus far, the finding across different models suggest that information gap does play a role in affecting a household's water handling behavior. Nevertheless, one potential issue that could arise when exploring the relationship between information gap and the water treatment behavior is the potential for endogeneity bias. This bias can arise if there is an overlap in the unobserved characteristics that determine the household's information gap and the likelihood of them treating their drinking water. Under such a scenario, an estimation of the probit model without accounting for endogeneity can lead to a biased estimate. Since the information gap (*INOFRMATION_GAP)* variable comprises of the household's perception of their water quality level and the actual water quality level, the endogeneity could potentially arise from either of these sources.

In fact, previous studies that have highlighted the role of perception in water handling behaviors have raised concerns about the endogeneity of the perception variable. One of the earlier papers to explicitly acknowledge the endogeneity of perception was by (Whitehead, 2006) to investigate the willingness to pay for water quality improvements in the Neuse River in North Carolina. This study used the household’s income, knowledge, tax amount, and water-related socioeconomic variables as an instrument for perceived water quality. More recently Lloyd-Smith et al. (2018) used perceived mortality risk from skin cancer as an instrument for perceived mortality risk from water consumption and suggest that not accounting for the endogeneity of the perception variable would have resulted in conservative estimates. Other studies that have explored the impact of perception on water averting behaviors by accounting for the potential endogeneity in perception include those by Nauges and Van Den Berg (2009); Onjala et al. (2014) and Vásquez et al. (2015). These studies have relied on instruments like the community perception of the household's water quality, and the households water source as instruments for water quality perceptions.

An approach to overcome the problem with endogeneity in a categorical variable case is by using the bivariate probit model (Greene, 2003). To circumvent the problem with the possible endogeneity in the information gap variable, we estimated a bivariate probit model as well (Table 3.8). However, one caveat to note in the estimation of the bivariate model is that while this model can account for the potential endogeneity of the information gap variable, it is not perfectly suitable for our study. The main objective of this study is to understand how the four different household groups vary in their water handling behavior. This bivariate model, however, is only suitable when the endogenous categorical variable is dichotomous. (In this study, there are four different household groups that arises from the difference between objective and perceived water quality: i.e., *Group 1: Ignorant and Optimist*, *Group 2: Aware and Optimist*, *Group 3: Aware and Pessimist*, *Group 4: Ignorant and Pessimist*). In order to estimate the bivariate model, the four household groups were converted to a dichotomous variable. The households with divergent gaps (Group 1 and

Group 4) were combined into a single group *(WIDE_GAP)*, and the households with minimal gaps (Group 2 and Group 3) were combined together *(MINIMAL_GAP)*. Since the bivariate model is not able to capture the true essence of our study, we use this model simply as another set of robustness check only.

We employed three set of instruments in the bivariate model to capture the potential endogeneity in the information gap variable (See Appendix 3.10). The first instrument considered is the average community perception which captures how drinking water risk is perceived by the community in the ward where the household lives (*COMM _PERCEPTION*). For e.g., if household *i* living in ward *j* drinks water from source *k,* we consider the average household perception of the water at source *k* in ward *j*. The second instrument we consider is the household's water source (*WATER_SOURCE*). We assume that average perception in the community and the water source are both good proxies for the households' perception of their water quality level, and thereby it affects the information gap variable. Both instruments have previously been employed in water averting literature to correct for the endogeneity in perception (Nauges and Van Den Berg, 2009; Onjala et al., 2014; Vásquez et al., 2015).

Our third instrument accounts for the possible endogeneity in the *INFORMATION_GAP* variable arising from the level of E. coli in the water. The third instrument considered is the frequency with which a household washes their drinking water storage vessel *(WASH_UTENSILS)*. Previous studies have indicated that household hygiene practices (such as frequently touching the water in the storage container with hands, or storing water in storage container for a long time period) could potentially increase the likelihood of E. coli contamination (Oswald et al., 2007; Roberts et al., 2001). Thus, the risk of E. coli contamination could be mitigated in households that frequently wash their storage vessels, thereby affecting the *INOFRMATION_GAP* variable in our analysis. We assume that the water vessel washing behavior is independent of the water treatment behavior[21]. About 62% of the households in our sample washed their water storage vessels every day (Table 3.1).

The estimate of the bivariate model is presented in Table 3.8. The finding from the bivariate model (Table 3.5) after accounting for the possible endogeneity in the information gap supports the result from the probit model. The result still loosely indicates that the households with minimal gap (*MINIMAL_GAP*) were more likely to treat their water relative to households with a larger gap between perception and objective water quality levels. The negative coefficient on the *COMM _PERCEPTION* variable suggests that households are less likely (more likely) to fall in the minimal gap category if the community perceives the households' water source to be risky (safe). The second instrument, *WASH_UTENSILS* suggests that households that regularly wash (do not wash) their drinking water storage container are less (more) likely fall in the minimal gap category. The third instrument included was the households water source (*PRIVATE_TAP, TUBEWELL, BORING*), but this variable was not significant. A brief discussion on the sign and significance of the instrument variables is presented in the Appendix 3.10. The

[21]The household survey was conducted during the summer season in Nepal when it gets very hot. As a result, we think most households are not inclined to boil their water and wait for it to cool down before drinking it. However, washing the storage vessel it not as much time-intensive as the former activity, thus, the relationship between the two is likely to be independent.

correlation estimate (ρ) is, however, not statistically significant, and the Wald test of $\rho = 0$ fails to reject at the 10% level which suggests that the error terms between the two equations in the bivariate model are actually not correlated. Likewise, the score test of normality ($\chi^2 = 33.09$) in the bivariate probit model also indicates that bivariate estimation may not be required for our model. Hence, while the bivariate model in Table 8 does suggest that the households with minimal divergence between perception and objective quality are more likely to treat their water even after accounting for the possible endogeneity, the result itself should be taken with caution. Nevertheless, the overall finding from the paper on the dissimilar water averting behavior of households with minimal gap to households with larger gap still remains valid.

3.7 Conclusion

The health consequences of poor water quality and inadequate supply in the developing world can be devastating. A cheap and effective solution to combat water contaminants can be in-home water treatment. This paper investigated the water averting behaviors at the household level in a developing country context, with particular emphasis on the gap between the households' perception and their objective water quality level. The finding indicates that the gap between perception and reality does play a role in a household's decision to employ water treatment measures. Households that had a wider divergence between perception and objective water quality levels, (i.e., *Group 1: Ignorant and Optimist* and *Group 4: Ignorant and Pessimist*) were less likely to treat their water and this result held across different specifications. In contrast, the household group that had a minimal gap between perception and objective quality (i.e., "Group 2: *Aware and*

Optimist" and *Group 3: Aware and Pessimist*) more were likely to employ water treatment measures.

The hypothesis that perception may not be the only determining factor that shapes households' water handling behavior was further confirmed when comparing households that had similar perceptions (Group 1 versus Group 2, and Group 3 versus Group 4). While households in Group 1 and Group 2 had similar (positive) perception, and likewise households in Group 3 and Group 4 had a similar (negative) perceptions of their water quality, the result indicated that households in Group 1 and Group 4 were both 25 percentage points less likely to treat their water than households Group 2 and Group 3 respectively. This evidence indicates that perception alone may not be the driving factor of averting behavior as previous studies suggest. The other findings in the paper suggest that households with private taps, those with children and households that had some college level education were more likely to treat their water. Conversely, households that were satisfied with the taste of their drinking water and rental households were also less likely to adopt averting behaviors.

The findings in this study present substantial evidence for policymakers to focus on two aspects to minimize the water-related health problems in the developing world: information provision and implementing programs designed to improve household perceptions of their water quality. Information provision is emerging as a useful policy tool in environmental risk management and could greatly expand water treatment adoptions in households. For instance, the government can implement programs whereby experts assess the level of contaminants in the drinking water of households and inform them about the health risks associated with drinking contaminated water. Information provided in a culturally salient format and in a systematic way has shown to be successful in changing behaviors (Balasubramanya et al., 2013; Bennear et al., 2013). Health education classes could be another approach that has proven to be quite effective in changing households' hygiene behaviors in Kerela, India (Cairncross and Valdmanis, 2006).

An alternative approach of information provision and dissemination on water quality levels could be to train the households to measure their water quality themselves. In fact, the *Nepal Study Center* at the University of New Mexico has recently implemented a "*citizen science*"[22] program where we have trained local volunteers in Siddharthanagar, Nepal to measure the contaminants in the nearby Danda River. This type of program can easily be extended to the household's drinking water as well, and it could improve the likelihood households engaging in water treatment behaviors. Households' that have been trained to measure their water contaminants would receive accurate information themselves without the need to rely on experts. Additionally, an approach to minimizing false perceptions on water quality levels could be to implement programs targeted to raise the awareness levels on safe practices for water, sanitation, and health. Likewise, forming water user groups in the community, providing training on management and accounting to these user groups, and creating incentives to send the children to schools could all be vital to reducing the information gap in the households and moving the society towards safer water practices.

[22] For more information, please visit: https://foxc01.wixsite.com/yogdan/projects

3.9 Figures and Tables

Table 3.1. Variable Definition and Descriptive Statistics

Variable	Definition	Mean	SD
Drinking Water Characteristics			
TREAT	If the household adopts any kind of treatment measures on their drinking water (1 = Yes, 0 = Otherwise)	0.34	0.47
BOIL	If the household's primary means of treating water is by boiling it (1 = Yes, 0 = Otherwise)	0.21	0.41
FILTER	If the household's primary means of treating water is by filtering it (1 = Yes, 0 = Otherwise)	0.06	0.25
PRIVATE_TAP	If the household uses private tap as their main source of drinking water (1 = Yes, 0 = Otherwise)	0.33	0.47
PUBLIC_TAP	If the household uses public tap as their main source of drinking water (1 = Yes, 0 = Otherwise)	0.16	0.37
TUBEWELL	If the household uses shallow tube-well as their main source of drinking water (1 = Yes, 0 = Otherwise)	0.38	0.48
BORING	If the household uses groundwater boring as their main source of drinking water (1 = Yes, 0 = Otherwise)	0.11	0.32
WATSATIS	If the household is satisfied with the taste of their drinking water (1 = Yes, 0 = Otherwise)	0.89	0.32
Socioeconomic Profile			
SCIKNOW	The scientific knowledge index of the respondent	0.49	0.25
COLLEGE	If the respondent had at least some college level education (1 = Yes, 0 = Otherwise)	0.18	0.38
SICK	If any member of the household had contracted a waterborne disease in the last 30 days (1 = Yes, 0 = Otherwise)	0.45	0.50
ETHNICITY	If the household belongs to a Brahmin or Chhetri caste (1 = Yes, 0 = Otherwise)	0.25	0.43
CHILD	If the household had at least one children under 5 years old (1 = Yes, 0 = Otherwise)	0.43	0.50
RENTAL	If the household lived in a rental place (1 = Yes, 0 = Otherwise)	0.14	0.35
WEALTH	The income of the household measured through an asset index (1 = Quartile 1; 2 = Quartile 2; 3 = Quartile 3)	1.98	0.83
URBAN	If the household belongs to the Siddharthanagar municipality (1 = Yes, 0 = Otherwise)	0.84	0.36
Water Quality Perceptions and Objective Level			
ECOLI_WATER	The presence of an E. coli bacteria in the households main drinking water source (1 = Yes, 0 = Otherwise)	0.34	0.47
QUALITY_PERCEPTION	The households' subjective perception of their drinking water before treatment (1 = No Risk; 2 = Little Risk; 3 = Some Risk; 4 = Serious Risk)	1.71	0.88
INFORMATION_GAP	The gap between the household's objective water quality level and their perception. Divided into four groups. (Group 1 = Positive water quality perception and presence of E. Coli; Group 2 = Positive water quality perception and absence of E. Coli; Group 3 = Negative water quality perception and presence of E. Coli; Group 4 = Negative water quality perception and absence of E. Coli.)	2.23	1.07

	Group 1 and Group 4 are the households with divergent gap. Group 2 and Group 3 are the households with minimal gap. [This is the Ri*Ei variable in the empirical analysis]		
COMM _PERCEPTION	The average perception of a household's water quality from other households that live in a particular ward. (1 = No Risk; 2 = Little Risk; 3 = Some Risk; 4 = Serious Risk)	1.70	0.40
WASH_UTENSILS	If the households washed their water storage container everyday (1 = Yes, 0 = Otherwise)	0.62	0.48

Figure 3.1: Households' perception of the quality of their drinking water

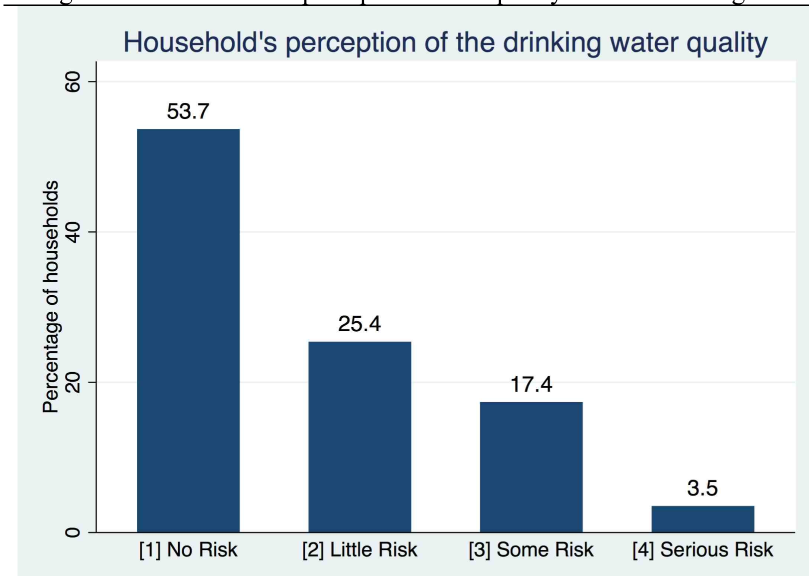


Figure 3.2: E. coli test on the households' drinking water

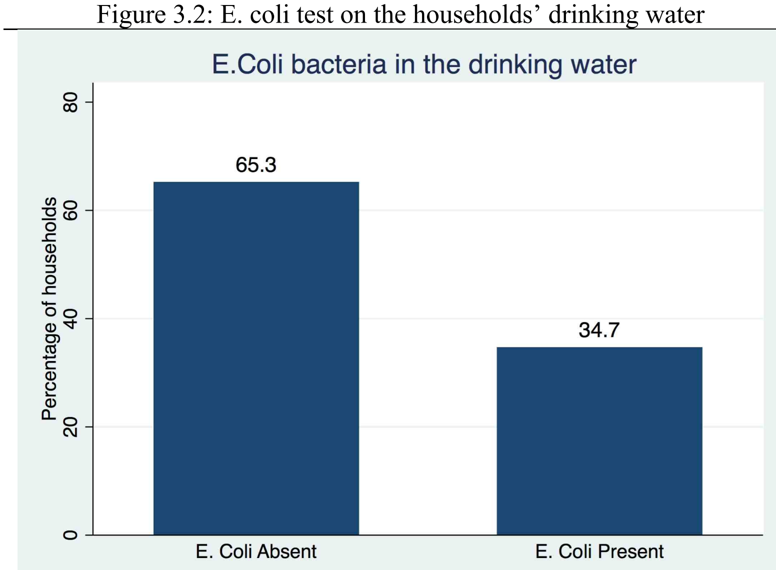


Figure 3.3: Household groups based on the perception and the actual water quality data. These four groups are derived from the *INOFRMATION_GAP* variable.

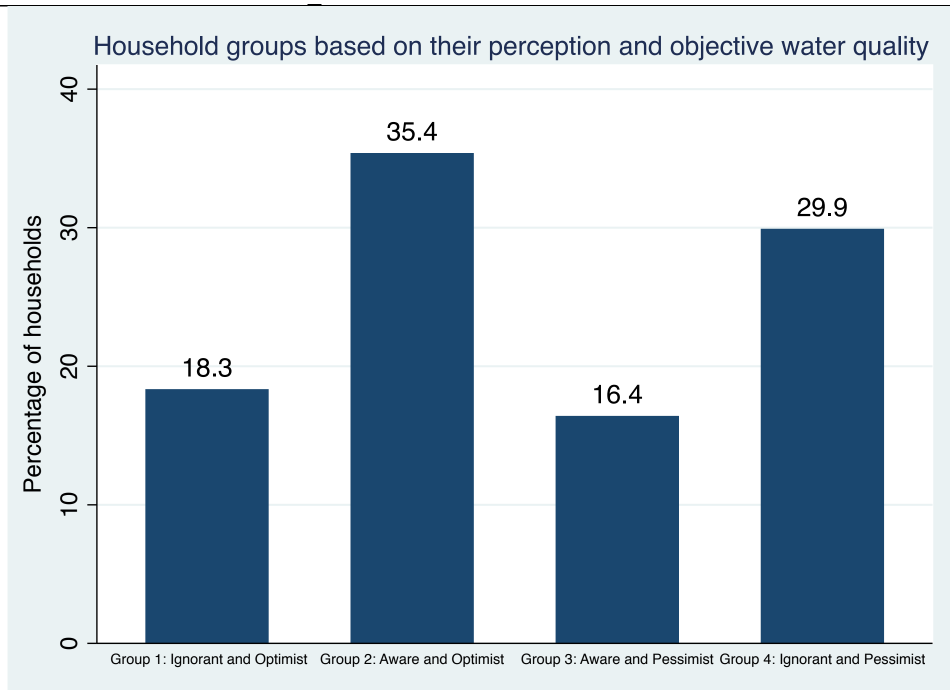
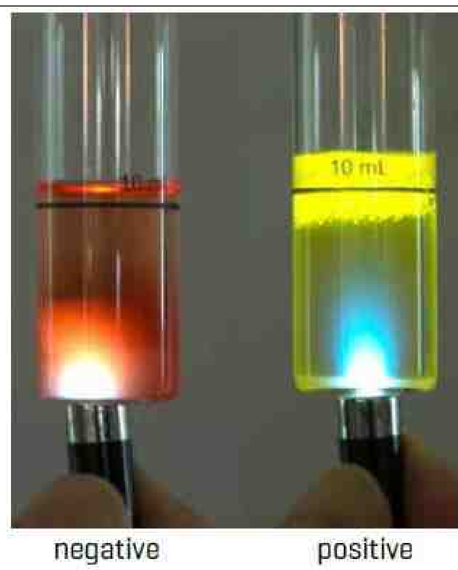


Figure 3.4: E. coli bacteria test sample.



A presence of the E. coli bacteria would cause the water sample to fluoresce with exposure to a UV light. The water sample in the right tested positive for the E. coli bacteria, while the one in the left did not contain the E. coli bacteria.

Table 3.2: Two-way table for subjective perception and objective water quality

	E. Coli Absent	*E. Coli Present*
No Risk	66.19%	33.81%
Little Risk	66.67%	33.33%
Some Risk	58.33%	41.67%
Serious Risk	60.00%	40.00%
Pearson χ^2 (3) = 1.1936; Pr = 0.755		Fisher's exact = 0.740

Table 3.3: Two-way table for water treatment behavior and the households' information gap

	"Group 1: Ignorant and Optimist"	*"Group 2: Aware and Optimist"*	*"Group 3: Aware and Pessimist"*	*"Group 4: Ignorant and Pessimist"*
No Treatment	33.82%	31.86%	11.27%	23.04%
Treat Water	22.43%	42.06%	26.17%	9.35%
Pearson χ^2 (3) = 21.7834; Pr = 0.000		Fisher's exact = 0.000		

Table 3.4: Basic Probit models of water averting behavior

	(1) TREAT	(2) TREAT	(3) TREAT
Group 1: Ignorant and Optimist	-0.3993* (0.165)		
Group 3: Aware and Pessimist	0.4136 (0.252)		
Group 4: Ignorant and Pessimist	-0.8818*** (0.182)		
ECOLI_WATER		-0.0272 (0.122)	-0.0345 (0.206)
RISK_PERCEPTION		0.1747^{+} (0.084)	0.4480* (0.200)
RISK_PERCEPTION * ECOLI_WATER			

Group 4 v/s Group 2			-0.3992*
			(0.165)
Group 1 v/s Group 2			-0.8818***
			(0.182)
Group 3 v/s Group 2			-0.4136
			(0.252)
Group 1 v/s Group 4			-0.4825
			(0.317)
Group 3 v/s Group 4			0.8129**
			(0.302)
Group 3 v/s Group 1			1.295***
			(0.305)
Intercept	-0.2073^{+}	-0.463**	-0.2073^{+}
	(0.116)	(0.149)	(0.116)
Observation	311	311	311

Notes: Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The table presents the result for the probit model of water averting behavior. The dependent variable in all three panel is the dichotomous variable *TREAT*. The first panel presents the results for the case when *TREAT* is regressed on the *INFORMATION_GAP* variable. The second panel presents the case when *TREAT* is regressed on the subjective and objective water quality levels. Finally, the third panel presents the result of the probit pairwise comparison when *TREAT* is regressed on the subjective and objective water quality levels and the interaction between the subjective and the objective quality level.

Table 3.5: Probit models of water averting behavior with different control variables

	(1) TREAT	(2) TREAT	(3) TREAT
ECOLI_WATER	-0.1092	-0.7624	-0.0653
	(0.221)	(0.207)	(0.225)
RISK_PERCEPTION	0.3783^{+}	0.3899^{+}	0.4190*
	(0.195)	(0.212)	(0.210)
RISK_PERCEPTION * ECOLI_WATER			
Group 4 v/s Group 2	-0.4373**	-0.4557*	-0.3707*
	(0.157)	(0.181)	(0.183)
Group 1 v/s Group 2	-0.9247***	-0.9219***	-0.8550***
	(0.209)	(0.187)	(0.179)
Group 3 v/s Group 2	0.2691	0.3137	0.3536
	(0.249)	(0.279)	(0.300)
Group 1 v/s Group 4	-0.4874	-0.4662	-0.4843
	(0.335)	(0.312)	(0.315)
Group 3 v/s Group 4	0.7064*	0.7694*	0.7243*
	(0.309)	(0.331)	(0.327)
Group 3 v/s Group 1	1.1940***	1.2356***	1.2085***
	(0.305)	(0.340)	(0.303)
<u>Water Characteristics</u>			
PRIVATE_TAP	0.2224	0.2497	0.2778^{+}
	(0.191)	(0.210)	(0.158)
TUBEWELL	-0.0931	-0.0814	-0.0984

	(0.211)	(0.226)	(0.194)
BORING	0.0061	-0.0727	-0.0035
	(0.431)	(0.411)	(0.353)
WATSATIS	-0.4381^{*}	-0.5019^{**}	-0.4826^{**}
	(0.195)	(0.172)	(0.177)
Knowledge & Health			
COLLEGE		-0.5601^{+}	0.5170^{+}
		(0.295)	(0.266)
SCIKNOW		0.3900	0.3206
		(0.255)	(0.266)
SICK		-0.1255	-0.1230
		(0.216)	(0.210)
Household Characteristics			
WEALTH: Quartile 2			0.1573
			(0.167)
WEALTH: Quartile 3			-0.2060
			(0.204)
ETHNICITY			0.2822^{+}
			(0.156)
CHILD			0.2088^{+}
			(0.117)
Location Characteristics			
RENTAL			-0.4935^{***}
			(0.149)
URBAN			0.1659
			(0.205)
Observation	311	311	311

Notes: Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The table presents the result for the probit model of water averting behavior. The dependent variable in all three panel is the dichotomous variable *TREAT*. The first panel presents the results by controlling for water characteristics. The second panel adds controls the variables associate with knowledge and health, while the third panel is the full probit model.

Table 3.6: Marginal Effect from the probit model of water averting behavior

	(1) TREAT	(2) Marginal Effects
ECOLI_WATER	-0.0653	-0.2040
	(0.225)	(0.0710)
RISK_PERCEPTION	0.4190^{*}	0.0578
	(0.210)	(0.058)
RISK_PERCEPTION * ECOLI_WATER		
Group 4 v/s Group 2	-0.3707^{*}	-0.1260
	(0.183)	(0.058)
Group 1 v/s Group 2	-0.8550^{***}	-0.2562
	(0.179)	(0.050)
Group 3 v/s Group 2	0.3536	0.1299
	(0.300)	(0.107)

Group 1 v/s Group 4	-0.4843	-0.1301
	(0.315)	(0.086)
Group 3 v/s Group 4	0.7243*	0.2560
	(0.327)	(0.107)
Group 3 v/s Group 1	1.2085***	0.3861
	(0.303)	(0.087)
Water Characteristics		
PRIVATE_TAP	0.2778^{+}	0.0910
	(0.158)	(0.049)
TUBEWELL	-0.0984	-0.0303
	(0.194)	(0.060)
BORING	-0.0035	-0.0011
	(0.353)	(0.111)
WATSATIS	-0.4826**	-0.1526
	(0.177)	(0.056)
Knowledge & Health		
COLLEGE	0.5170^{+}	0.1634
	(0.266)	(0.080)
SCIKNOW	0.3206	0.1013
	(0.266)	(0.082)
SICK	-0.1230	-0.0389
	(0.210)	(0.065)
Household Characteristics		
WEALTH: Quartile 2	0.1573	0.0513
	(0.167)	(0.555)
WEALTH: Quartile 3	-0.2060	-0.0632
	(0.204)	(0.061)
ETHNICITY	0.2822^{+}	0.892
	(0.156)	(0.050)
CHILD	0.2088^{+}	0.0660
	(0.117)	(0.035)
Location Characteristics		
RENTAL	-0.4935***	-0.1560
	(0.149)	(0.040)
URBAN	0.1659	0.0524
	(0.205)	(0.065)
Observation	311	

Notes: Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The first panel presents the probit results for the averting behavior model. The dependent variable is the dichotomous indicator for water treatment, TREAT. The second panel is the marginal effects of the probit model. The significance (asterisks) in the marginal effects have been suppressed.

Table 3.7: Probit models of water averting behavior: Different mode of treatment

	(1) TREAT	(2) Boil	(3) Filter
ECOLI_WATER	-0.0653	-0.1395	-0.0175
	(0.225)	(0.197)	(0.075)
RISK_PERCEPTION	0.4190*	0.5627*	-0.0544

	(0.210)	(0.250)	(0.288)
RISK_PERCEPTION * ECOLI_WATER			
Group 4 v/s Group 2	-0.3707*	-0.6363**	-0.9813**
	(0.183)	(0.166)	(0.328)
Group 1 v/s Group 2	-0.8550***	-1.0595**	-0.9093*
	(0.179)	(0.372)	(0.364)
Group 3 v/s Group 2	0.3536	0.7022**	0.3686
	(0.300)	(0.213)	(0.318)
Group 1 v/s Group 4	-0.4843	-0.4232	0.0720
	(0.315)	(0.397)	(0.589)
Group 3 v/s Group 4	0.7243*	1.3386***	0.9445^{+}
	(0.327)	(0.218)	(0.496)
Group 3 v/s Group 1	1.2085***	1.7618***	0.8724*
	(0.303)	(0.454)	(0.393)
Water Characteristics			
PRIVATE_TAP	0.2778^{+}	0.2259	-0.1638
	(0.158)	(0.221)	(0.336)
TUBEWELL	-0.0984	0.0973	0.0397
	(0.194)	(0.254)	(0.261)
BORING	-0.0035	0.3415	-0.0311
	(0.353)	(0.376)	(0.382)
WATSATIS	-0.4826**	0.1480	-0.3152
	(0.177)	(0.261)	(0.270)
Knowledge & Health			
COLLEGE	0.5170^{+}	0.2423	-0.1964
	(0.266)	(0.380)	(0.264)
SCIKNOW	0.3206	-0.1284	0.1372
	(0.266)	(0.3399)	(0.388)
SICK	-0.1230	0.2014	-0.0042
	(0.210)	(0.162)	(0.205)
Household Characteristics			
WEALTH: Quartile 2	0.1573	0.0063	0.6643*
	(0.167)	(0.187)	(0.275)
WEALTH: Quartile 3	-0.2060	0.0447	0.3206
	(0.204)	(0.293)	(0.249)
ETHNICITY	0.2822^{+}	0.3908*	0.4937^{+}
	(0.156)	(0.164)	(0.277)
CHILD	0.2088^{+}	0.2026	0.0523
	(0.117)	(0.177)	(0.170)
Location Characteristics			
RENTAL	-0.4935***	-0.2750	-0.6684
	(0.149)	(0.249)	(0.419)
URBAN	0.1659	-0.1233	-0.2577
	(0.205)	(0.253)	(0.405)
Observation	311	311	311

Notes: Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The table presents the result for the probit model different mode of treatment. The first panel presents the results for any mode of treatment, the second panel presents when the households primarily boiled their water, the third panel lists the output when the primary mode of treatment was filtration.

Table 3.8: Bivariate Probit model of water averting behavior

	Bivariate probit (TREAT)
Household Group: *MIN_GAP*	0.5911*** (0.113)
Water Characteristics	
WATSATIS	-0.5979** (0.172)
Knowledge & Health	
COLLEGE	0.5119+ (0.276)
SCIKNOW	0.4333 (0.283)
SICK	-0.0615 (0.154)
Household Characteristics	
WEALTH: Quartile 2	0.0690 (0.145)
WEALTH: Quartile 3	-0.2277 (0.191)
ETHNICITY	0.2116 (0.132)
CHILD	0.2272+ (0.126)
Location Characteristics	
RENTAL	-0.5231* (0.194)
URBAN	0.2352 (0.206)
Intercept	-0.3306 (0.313)
Instrument Variables	
COMM _PERCEPTION	-0.7290*** (0.191)
WASH_UTENSILS	-0.3333*** (0.165)
PRIVATE_TAP	-0.0699 (0.374)
TUBEWELL	-0.0888 (0.217)
BORING	-0.1018 (0.353)

WATSATIS	0.6595*
	(0.291)
COLLEGE	0.0405
	(0.190)
SCIKNOW	0.9346*
	(0.388)
SICK	0.5889**
	(0.215)
WEALTH: Quartile 2	-0.0487
	(0.205)
WEALTH: Quartile 3	0.3244
	(0.258)
ETHNICITY	-0.4528+
	(0.258)
CHILD	0.2056
	(0.223)
RENTAL	-0.2896
	(0.413)
URBAN	0.6938
	(0.487)
Intercept	-3.0199***
	(0.813)
Observation	311
Fisher's Z transformation	0.189
	(0.165)
ρ	0.186
Wald test of ρ= 0 χ^2	1.306
SCOREGOF test (χ^2)	33.09

Notes: Robust standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the bivariate probit results for the averting behavior model. The dependent variable is the dichotomous indicator for water treatment, TREAT. The information gap is captured by HOUSEHOLD GROUP: *MIN_GAP* variable. Three instruments have been used to account for the possible endogeneity of this variable: COMM _PERCEPTION, WASH_UTENSILS and water source (*PRIVATE_TAP, TUBEWELL, BORING)*.

3.10 Bivariate Probit

The empirical specification for the bivariate model is given by:

$$y_i^* = (INFORMATION\_GAP) * \theta_i + X_i\beta_i + \varepsilon_i \quad (12)$$

$$(INFORMATION\_GAP)^* = Z_i\emptyset + X_i\beta_2 + v_i$$

Where, y_i is the dichotomous water treatment behavior *(TREAT)*, $(INFORMATION\_GAP)$ is the gap between the households perception and objective water quality level, X_i are the socio-economic characteristics and Z_i is a vector of identifying restrictions. The error terms ε_i and v_i in equation 6 are jointly distributed as bivariate normal with mean zero, a non-zero variance-covariance, and correlation ρ_i = Corr (ε_i, v_i). If ρ_i is not equal to zero, then ε_i and $(INFORMATION\_GAP)$ are correlated, and a probit estimation is inconsistent for β and θ in the first equation. The parameter of interest for the bivariate estimation are β_1, θ, β_2, and $\emptyset$. The correct specification of the bivariate model requires identification of restrictions that are significant determinants of the endogenous variable $(INFORMATION\_GAP)$ and also orthogonal to the residual of the main equation, ε_i.

<u>Discussion of the sign and significance of the Instrument Variable from Table 8:</u>

Before moving to the relationship between the instruments and the endogenous variable, it should be noted that the first instrument (COMM_PERCEPTION) is likely to have a positive impact on the household's own perception. If the community views the household's water source as risky (safe), the household is also likely to view it similarly.

Similarly, the second instrument (WASH_UTENSIL) is likely to negatively affect the household's hygiene. Households that wash their utensils more frequently are less likely to have their water contaminated with the E. coli bacteria. Using these two relationships, the result of the instruments can be interpreted as follows:

The *minimal gap* households are those that considered their water to be safe (risky), and the test revealed the water was actually safe (risky) because of the absence (presence) of the E. coli bacteria. If the community perceives the households water source to be risky, the household also considers it to be risky. This means the household's perception of their water quality is negative.

On the other hand, if the household washes their utensils frequently, they are not likely have the E. coli bacteria. In this scenario, the households perception is negative, but the water quality is actually positive. Thus, when the community considers the household's water source to be risky and if the household washes their utensil frequently, they are less likely to be in the minimal gap group. The third instrument, source of the water, was not significant in Table 3.8.

Chapter 4: Assessing the Impact of Climate Change on Farmland Values in Nepal

4.1 Introduction

Climate change is emerging as a significant threat facing the humanity in the 21st century. There is a consensus among researchers that variations in land and water regimes through changes in climate might pose a significant challenge to the natural and human systems. Agriculture is one area that is highly sensitive to climate due to its reliance on weather patterns and climate cycles for productivity. Agriculture is also the principal use of land globally with approximately 1.2-1.5 billion hectares of lands under crops, while another 3.5 billion hectares are used for grazing (Howden et al., 2007).

The impact of climate change on agricultural productivity are perhaps more acute in the developing world. Since the majority of the developing countries depend heavily on rain-fed agriculture, the effects of climate change on productive croplands are likely to threaten both the welfare of the population and the economic development of these countries. One nation that is predominantly dependent on agriculture is Nepal. With 82.5% of the population living below the international poverty line of $2 per day (World Bank 2003), Nepal is one of the poorest countries in the world. In the late 1980s, agriculture was the livelihood for more than 90 percent of the population, and while only approximately 20 percent of the total land area was cultivable, it accounted for, on average, about 60 percent of the GDP and approximately 75 percent of exports (Savada, 1991). While the dependence on agriculture has declined somewhat since 1990 when 52% of the country's GDP came from agriculture, farming is still one of the primary occupations of people residing in Nepal. Such a heavy reliance on agriculture makes Nepal's economy very sensitivity to climate variability.

Past studies suggest that the average annual mean temperature in Nepal has increased at an annual rate of .06^{0} C between 1977 and 2000 (Malla, 2009). It has subsequently led to changes in the frequency of temperature extremes with more frequent warmer days and nights; and less frequent colder days and nights (Gum et al., 2009). Precipitation, on the other hand, has not displayed any definitive trends, but evidence indicates an increasing occurrence of intense rainfall events and rising flood days over the years (Gum et al., 2009). Such instances of extreme temperature and precipitation can result in desirable agricultural land being undesirable as crop yields are restricted. In fact, these changing climatic conditions have led to shifts in cropping patterns and the agricultural sector in Nepal is consequently being severely hurt. Regmi (2007) indicated that the eastern region of Nepal faced rain deficit in 2005/06 and the crop production was reduced by 12.5% on a national basis. Likewise, while Nepal used to be rice exporter in the past, the fluctuating climate conditions has limited the rice yields, and as a result, Nepal has been a rice importer for the past few years.

Nepal's heavy dependence on rain-fed agriculture coupled with the potential distressing effect of climate change, and ultimately on the welfare of the population and the economy of the country itself, necessitates a thorough analysis on the economic impact of climate change on the agricultural sector. An exhaustive assessment of the economic impact would allow for new policy formulation on potential mitigation and adaptation strategies to combat the likely effects of climate change. In this paper, an application of the Ricardian approach[23] (Mendelsohn et. al 1994) is used to evaluate the economic impact of climate change on agricultural productivity in rural Nepal. This paper differs from previous work on Ricardian approach literature in that the effect of climate change is analyzed by treating the choice of irrigation as endogenous. It is possible that a farmer's decision to employ irrigation in farmlands is influenced by various factors, one of which could be the climatic conditions itself. There have been very few works that have employed the Ricardian approach in Nepal, and none that treats the choice of irrigation as endogenous.

We build an endogenous irrigation model that recognizes the potential of sample selection bias (Heckman 1979). In the first stage, we estimate the probability of irrigation including climate, district flows, and other exogenous variables. In the second stage, we estimate the land value for the rainfed and irrigated farming including a sample selection correction term. We test this model using a sample of over 1165 plots across 27 districts in Nepal. The empirical results reveal that the choice of irrigation is endogenous. The results indicate that Nepalese farmlands are sensitive to climate change. Irrigated farmlands

[23] The fundamental idea of the Ricardian approach is that land values and agricultural practices are correlated with an environmental variable, climate. However, some assumptions underlie this framework. The Ricardian model assumes that farmers are rational utility maximizers and relies on an existence of a competitive economy with perfectly functioning output and input markets. With these assumptions, the Ricardian framework asserts that if the optimal use of farmlands is agricultural production, then the observed market rent on a parcel of land should equal the annual net profits from the production of an agricultural commodity using that land (Mendelsohn et al., 1994). Thus, farmland values are the discounted value of current and future profit. Furthermore, we can observe the relationship between farm values to climate and other variables to infer the optimal use of land. Hence, depending on the positive and negative impact of climate variables, the long-run accumulation of net profit defines land value.

were found to have a higher land value when the temperature and rainfall increased during summer season. Dry lands, on the other hand had a reduction in land value due to an increase in temperature and rainfall during spring season. This result indicates that irrigated farmlands can be an effective adaptation mechanism to protect agriculture from erratic changes rainfall and temperature.

4.2 Literature Review

Mendelsohn, Nordhaus, and Shaw (1994) developed a model of climate-land value relationship to assess the impact of climate change on farmland values in the United States. They evaluated the efficacy of the traditional production function approach in estimating the impacts of climate change with a new method they developed, the '*Ricardian Method*'[24]. The production function approach is based on the crop simulation models where the climate change impacts are estimated by varying input variables, including the climate itself. Mendelsohn et al. (1994) suggested that the limitation of the production-function approach in failing to account for the numerous substitutions and adaptations that farmers make could lead to an inherent bias that results in an overestimation of the damages from climate change. The Ricardian method, on the other hand, was developed on the assumptions of rational utility-maximizing farmers, perfectly competitive markets and an equal rate of capital per acre, interest rate and rate of capital gain for all parcels (Mendelsohn et al., 1994). Under such a scenario, farm value represents the present value

[24] The Ricardian Method is named after the influential classical economist David Ricardo (1772 – 1823), who argued that in a perfectly competitive market, land values would reflect land profitability.

of future profits in the Ricardian analysis. Their proposed model was applied in a cross-section study of 48 states in the US to measure the effect of climate variables on agriculture.

Ricardian models have since been used in numerous to study the impact of climate change on agricultural productivity both in the developed and the developing nations. For instance, Kumar and Parikh (1998) find that a temperature increase of 2 ^{0}C and an accompanying precipitation increase of 7% can lead to a 9% decrease in the farmland revenue in India. Other studies that have implemented the Ricardian approach to explore farmland productivity in different parts of the world include those by Mendelsohn (2000) in the Great Britain; Reinsborough (2003) in Canada; Seo et al. (2005) in Srilanka; Fleischer et al. (2008) in Israel; Wang et al. (2009) in China; Kurukulasuruya et al. (2006) in Africa; and Kunwar & Bohara (2017) in Nepal. These studies have all suggested that changes in temperature and precipitation can affect the farmland values. While the Ricardian method has since garnered widespread attention, there have been some notable criticisms as well because of the strong assumptions it makes (Cline, 1996; Fisher & Hanemann, 1998; Darwin, 1999; Quiggin & Horowitz, 1999; Polsky, 2004; Deschenes and Greenstone, 2007). Darwin (1999) maintained irrigation to be an essential variable and omitting it would make the model of Mendelsohn et al. (1994) inconsistent with the Ricardian principle. Cline (1996) argued that the assumption of fixed relative prices in the Ricardian approach makes it a partial-equilibrium analysis. Besides, Cline (1996) also contended that the assumption of infinitely elastic supply of irrigation at current prices is misleading. Fisher & Hanemann, (1998) demonstrate that the omission of irrigation from the analysis can lead to an incorrect estimation of climate parameters' signs and magnitude.

Polsky (2004) argued that because Ricardian models are strongly aligned with perfect adaptations assumption, the negative impacts are biased to be small.

Among the various criticisms of the Ricardian approach, one issue arises from the choice of irrigation in affecting farmland values. Mendelsohn & Dinar (2003) quantified the role of irrigation in adapting to unfavorable climate conditions by comparing the climate sensitivity of irrigated and rain-fed cropland. They find that irrigated croplands were less sensitive to changes in precipitation unlike the drylands. The decision to employ irrigation, nevertheless, is affected by many factors. For instance, the choice of irrigation can be influenced by factors such as surface flows, soil types, subsidies and even the climate itself. Thus, studies that fail to account for the irrigation choices can lead to unreliable estimates of climate change impacts on agriculture due to potential endogeneity. In fact, the potential for endogeneity arising from irrigation choices remains one major concern in the Ricardian studies, and many previous studies have often overlooked this problem. One of the earlier papers to explicitly incorporate the endogeneity of irrigation choice was by Kurukulasuriya & Mendelsohn (2007). This paper developed a choice model of irrigation in the context of a Ricardian application, and the findings suggest that using irrigation as an exogenous choice can result in biased welfare estimates. Similarly, Kurukulasuriya et al. (2011) explicitly modeled irrigation choice as a function of climate to explore impact across 11 African countries using a sample of over 10,000 plots. They find that the choice of irrigation was endogenous and irrigation was an important adaptation strategy to climate if there was sufficient flow of water.

In the case of Nepal, there have been few Ricardian studies, but none that have incorporated the potential bias from treating irrigation exogenous. Kunwar & Bohara (2017) estimate the impact of climate change on Nepalese agriculture by incorporating spatial methods in the estimation of Ricardian model. The findings suggest that Nepalese farmlands are sensitive to climate change, and this result was consistent in both the non-spatial and the spatial frameworks. The inclusion of the spatial effects, however, revealed the presence of positive spatial autocorrelation and produced conservative estimates of climate change impacts. The net effect of annual increases in average temperature was negative; while the net effect of higher annual average precipitation was a positive outcome on farmland values. The marginal effect of every degree increase in average annual temperature was found to be $1.80/hectare reduction in farmland values. Likewise, for rainfall, it was found that 1mm increase in average annual rainfall would positively affect farmland value by $2.25/hectare. Finally, the findings also suggested that extreme weather events could also impact the agricultural productivity and the farmland values. However, the issue with this study is that it treated the choice of irrigation as exogenous and thus might not provide an accurate reflection of the true impacts of climate change.

In this paper, we take into account one of the criticisms of the Ricardian approach that has often been overlooked: the bias that might arise by treating irrigation as exogenous. To our knowledge, there have not been other studies in the context of Nepalese agriculture that have addressed the problem with endogenous irrigation choices. A Heckman sample selection model is employed to control for irrigation choices and to investigate the effect of climate change on the Nepalese farmlands. The following section discusses the data and the variables, the theoretical and empirical framework, and the findings of our analysis.

4.3 Data and Methods

This paper uses data from the Nepal Living Standard Survey 2010/2011 (NLSS III) of the Central Bureau of Statistics, Nepal. The methodology applied in the NLSS III was used in more than 50 developing countries by the World Bank with the purpose of the Government to monitor progress in improving the living conditions and to evaluate the impact of government policies in the country. The survey included a wide range of topics related to household welfare and the important socio-economic variables necessary were obtained from here. The survey data consisted of 5988 households covering 75 districts of Nepal. However, for the purpose of this study, only 1165 households in 27 districts have been used. The variables used in this study from NLSS include the age, gender, education level, credit amount for farmlands, distance to agriculture input market, farm size household size and access to electricity have been used. Age, gender and education level reflect the data for the head of household.

The data for temperature, rainfall and elevation for the 27 districts used were obtained from the department of hydrology and meteorology, Nepal. This paper used the standardized average of a long time-series temperature and rainfall data from 1972-2008 for 27 stations. Soil data was obtained from Food and Agriculture Organization (FAO). The FAO data provides information on the major and minor soils in each location.

4.3.1 Dependent variables

The dependent variables are the land value of farms as perceived by farmers who own it and the decision by farmers to employ irrigation in their farmland. (Mendelsohn et al. 1994) suggested that land values should be modeled as function of climate, soil and socio-economic variables in studying the impacts of climate change on agricultural production. While many authors have used net revenue or net profits as a proxy for land values (Kumar & Parikh 2001; Mendelsohn et al.2003; Mendelsohn et al. 2003 etc.), this paper uses the monetary amount assigned to farmlands owned by farmers if they were to sell it in the current market as land value. Land value has been converted to logarithm form to get a normally distributed function since the land values were highly skewed to the left. Similarly, '*Irr_choose*' is used as a binary dependent variable in the selection model and it captures farmer's decision to adopt irrigation in their farms. A value of 1 reflects farmlands that use irrigation and a value of 0 reflects farmlands that do not have irrigation.

4.3.2 Explanatory variables

Climate variables:

In the Ricardian analysis, climatic variables are included among the regressors along with soil and socioeconomic variables to simulate climate change. (Mensdelsohn et al 1994) hypothesized climate variables to have a linear and quadratic forms, where the linear term reflects the marginal value of climate evaluated at the mean, and the quadratic term captures how the marginal effect will change as one moves away from the mean. The climate variables (Precipitation and Temperature) for this study have been divided into 4 major seasons of Nepal: Fall, spring, summer and winter. The data for the climate variables has been standardized by the following formula:

$$Mean\ Climate = \frac{Mean_{2003-2008} - Mean_{1970-2008}}{Standard\ Deviation_{1970-2008}}$$

The variables for climate in this study take a linear and quadratic form. The quadratic climate variables are calculated by taking the square of the mean climate values. '*Elevation*' represents the geometric height of a district above the sea level, where the household has farmland, and it has been converted to logarithmic form.

Soil variables:

Soil variables are an important component of climate impact analysis as different areas differ in the soil characteristics and hence differ in crops that can be grown. Kumar & Parikh (2001) used two sets of soil dummies, one representing soil classes and other top soil depth class to address the problem of lack of quantitative soil data in their study. In this paper, '*Soil type*' is a categorical variable that captures the quality of soil in a particular district and it has been separated into 'good, moderate and bad' quality. The major soils found in the 27 districts for this paper were Eutric cambisols, Dystric cambisols,Vertic cambisols, Calcaric cambisols, Regosols, Leptosols, Fluvisol, Gleysol and Phaeozems. (FAO) lists Cambisols as soils that are good for agricultural land and as a result are intensively used in farming. Phaeozems are also listed as fertile soils that have a wide range of farming purposes. This paper has categorized the cambisols and phaeozems as the *high-quality* soils. Regosols are considered for capital intensive farming as well as low volume grazing. Gleysols are considered soils that lack wetness, but nevertheless are used for rice plantation. Regosols and Gleysols are categorized as *moderate-quality* soil in this paper. Lastly, Leptosols and Fluvisol are both considered unattractive soil that are used basically for grazing purposes and these soils are categorized as *low-quality* soils.

Socio-economic variables:

Based on previous studies that dealt with the Ricardian analysis (Mensdelsohn et al. (2007); Kumar et al. (2001); Mano et al. (2007)), socio-economic economic variables used in this study were age, gender, education level, household farm size, distance to input market, household size, access to electricity and credit amount received for farming. '*Credit Amount*' represents the total amount of loan a household has acquired for agricultural purposes. '*Distance to input market*' is the total kilometer distance from the respondent's farmland to the nearest agricultural center. '*Age*' and '*Gender*' represents the age and sex of the household head. '*HH size*' is the total number of members in a household and is used as a proxy for farm workers. The variable has been converted to logarithmic form because productivity is expected to fall as households become too large. '*Electricity*' represents whether a household has access to electricity or not and is used as a dummy variable. Finally, '*Education*' has been converted to a dummy variable and it captures whether the respondent if literate or not.

4.4 Theoretical and Empirical Framework

The Ricardian method is a cross-sectional approach to studying agricultural production using climatic variables and net revenue or the value of land. Farm performance

(Net revenue or land value) is regressed on a set of agro-climatic and socio-economic variables to assess the impact of climate change on farm performance. (Mendelsohn et al. 1994) argued that the previous method used to measure the impacts of climate change on agriculture, the production function approach, was a crop specific analysis and it tended to overestimate the impacts. To overcome the limitations from the earlier method, Ricardian approach was developed which assumes the following specification (Mendelsohn 1994):

$$V = \int P_{LE} e^{-\rho t} \partial t = \int (\sum P_i Q_i(X, F, Z) - \sum RX) \; e^{-\rho t} \partial t$$

Where, farmland value (V) reflects the present value of future net productivity; P_{LE} is the net revenue per hectare; P_i is the market price of the crop i, Q_i is the output of the crop i; F is a vector of climatic variables; Z is a vector of soil and economic variables; X is a vector of purchased inputs (excluding land); R is a vector of input prices; t is the time and ρ is the discount rate. The model is based on the assumption of a perfectly competitive market for both outputs and inputs; and the interest rate, rate of capital gains and capital per acre equal for all plots of land (Mendelsohn 1994). These assumptions allow for the reduction of the profit maximization function to a cross-sectional analysis.

Assuming a farmer that wishes to maximize his/her land value by choosing X given the characteristics of the firm and market prices, the Ricardian method is a reduced form model of the endogenous variables (F and Z) that examines their effect on the farm value. The standard Ricardian model hypothesizes a quadratic relationship between the land value (net revenue) and climate variables.

$$V = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 Z + \varepsilon$$

Where, ε is an error term. The linear and a quadratic term for temperature and precipitation accounts for the nonlinear shape of the net revenue of the climate response function. A positive quadratic term signifies a U-shaped net revenue function while a negative term implies that the function is hill shaped.

In order to conduct the econometric estimation, this paper relies on an approach similar to the sample selection model for labor (Heckman 1979). The Heckman technique estimates a two stage model to correct for sample selection bias. First, a selection equation is formulated with a dichotomous dependent variable equaling 1 for observed and 0 for missing values. The second stage is the outcome equation predicting the model's dependent variable. This stage also includes an additional variable- the inverse Mills ratio, derived from the probit estimate.

For this paper, a dichotomous choice model of irrigation, Y*, was estimated in the first stage, where Y* = 1 for irrigated farms and Y* = 0 for dry land farming. The following equation is considered for the selection estimation:

$$Y_i^* = \beta\Theta + u_1$$

$$\begin{pmatrix} Y_i^* = 1\,;\text{Irrigated farms} \\ Y_i^* = 0;\text{Dryland farms} \end{pmatrix}$$

In the second stage, a conditional function of land value is estimated for each type of farming based on the available exogenous variables, φ.

$$V^I = \Omega^I \varphi^I + u_2 \text{ if Y* = 1}$$

$$V^D = \Omega^D \varphi^D + u_3 \text{ if Y* = 0}$$

Y_i^* is a latent variable explaining the choice of irrigation, V^I is the land value of farms that have chosen irrigation, V^D is the land value of farms that have dry land farming, ϴ is a k vector regressors, φ^I is an m vector regressors for irrigation, φ is an m vector regressors for dry land, and the error terms u_1, u_2 and u_3 are assumed to be jointly normally distributed, independently of ϴ and φ, with zero expectations.

$$u_1 \sim N(0,1)$$

$$u_2 \sim N(0, \sigma_2)$$

$$u_3 \sim N(0, \sigma_3)$$

$$\text{corr } (u_1, u_2) = \rho_2$$

$$\text{corr } (u_2, u_3) = \rho_3$$

If ρ = 0, OLS (Ordinary Least Squares) regression provides unbiased estimates while $\rho \cong 0$ means OLS estimates are biased (Heckman 1979). The mills ratio from the selection model is employed in both the irrigated and dry land conditional regressions in order to control for selection (Dubin & McFadden 1984). I expect the signs on the coefficient of the estimated Mills ratio to be opposite for the two sets of farmlands. The estimated Mills ratio is used as an explanatory variable in the outcome model and a significant value of Mills ratio confirms its inclusion as a necessary regressor to avoid sample selection bias. This result means that the selection model provides consistent, asymptotically efficient estimates for all parameters in the model (Dubin &McFadden 1984). Mills ratio thus provides information on whether farms irrigate or not to improve the estimates of the parameters in the regression model.

4.5 Results

An empirical analysis using the Heckman's procedure was conducted in order to endogenize the choice of irrigation and to estimate the effect of climate variations on farmland value. In the first stage of the analysis, a probit model was run with irrigation choice (dryland v/s irrigated) as the dependent variable. The explanatory variables in the probit model were the linear standardized rainfall and temperature variables. The exclusion of the quadratic climatic variables resulted in a better fit when compared to only quadratic climatic variables, so the probit estimation included only linear terms for the climatic variables. Type of soil is a categorical variable and was used in the selection model as a control variable.

The results from the selection equation (Table 4.2) revealed that other than winter temperature and spring precipitation, the climatic and soil variables had an influence in a household's decision to employ irrigation. The coefficients for climate variables suggest that the probability to adopt irrigation increased with higher temperature during summer and greater precipitation during summer and fall. Similarly, higher winter rainfall and higher temperature during spring and fall led to a lower likelihood of a household adopting irrigation. The soil variables suggest that the probability of using irrigation was higher in areas where for moderate and high-quality soils, in comparison to the low-quality soil.

The second stage of the Heckman model, outcome equation, estimates the land value conditional on the decision to adopt irrigation or use dry land. The coefficients of the probit model were used to estimate the Mills ratio, which was the used as an additional explanatory variable in the outcome model. The coefficient on the Mills ration was significant and positive in the Irrigated farms, but insignificant in dry land farms. Table (4.3) shows the results from the outcome equation using ordinary least squares (OLS) method. The OLS regression has been used to examine the estimates on both, the dryland and irrigated land. In accordance with the Ricardian approach, the set of linear and quadratic climatic variables, soil types and various socio-economic variables have been used as the independent variables while the log of land value is the dependent variable.

The results from OLS regression in Table (4.3) supports the hypothesis that the land value in dry land and irrigated lands are different. The coefficients from the climate variables provide important insights into the climate sensitivity of farms. From the OLS regression (table 4.2), the linear terms of the temperature and precipitation variables in summer were positive for irrigated farms, whereas for dry land farms, higher temperature during spring and fall resulted in lower land value. However, higher precipitation during spring and fall for irrigated farms had a positive impact on land values. The results from the beta-coefficients showed that while higher winter and spring temperature led to a decline in land values for both irrigated and dry land farms, the impacts were different. In winter, 1 standard deviation increase in temperature led to a 1.5-unit standard deviation decrease in land value for irrigated farms but only 1.1-unit standard deviation decline for dry land farms. Similarly, during the spring season, 1 standard deviation increase in temperature led to 3.5-unit standard deviation decline in dry land values but only 1.8-unit standard deviation decrease for irrigated farms.

The quadratic variables that were significant imply that the relationship between climate and farm land values have a nonlinear relationship, which is consistent with the hypothesis of Ricardian approach (Mendelsohn et al. 1994, 1996). The positive coefficients in the quadratic terms for winter temperature in irrigated land suggests that there was a minimally productive level of temperature and either more or less temperature would increase land values. The negative quadratic coefficients for temperature and precipitation in both the dry land and irrigated land indicates that there is an optimal level of climate variable from which the value function decreases in both direction (Mendelsohn et al. 1994, 1996). The marginal impacts of temperature and precipitation calculated at the mean level revealed significant seasonal impacts (table 4.4, 4.5, 4.6, and 4.7). The results show that the overall impacts of climate as measured by marginal impact is similar in both the dry land and irrigated land, although the quantitative estimates vary. In both the models, the impact of higher temperature in winter and spring was harmful for the crops and it resulted in a lower land value. Higher temperature in fall also had a negative marginal impact on the land value for irrigated lands. The marginal impact of precipitation was not significant in dry land farms, while in irrigated farms, higher precipitation during summer, spring and fall were associated with higher land values.

The OLS estimates from the soil variables (Table 4.3) were significant and positive for irrigated farms but not for dry land farms. Better soil quality had a positive impact on farmland values as expected, however the interesting result was that irrigated farms with moderate soil quality resulted in 3.4 standard deviation increase in land values compared to good quality soil which resulted in only 2 standard deviation increase in land value. This result, although surprising, suggests that the lands with moderate soil quality could be used not only for agriculture but for other purposes as well. While good quality land is best for agriculture, a moderate soil quality lands could have residential/business use as well and this might have resulted in a higher land values of land with moderate soil quality. The estimates from elevation (Table 4.3) were negative and significant in both dry land and irrigated farms although the negative impacts were more pronounced in dry land farms compared to irrigated farms.

The estimates from the socio-economic variables (Table 4.3) showed that the distance to input market were negative and significant for the sets of land. While irrigated farms had 2.5% decline in farmland values due to a kilometer increase in the distance to input market, dry land farms had 3% decline in value. Age, education and household size were all positive and significant only in the irrigated farmlands. The coefficient of education variable implies that literate people could have more knowledge on the efficient management of irrigation in farms and that could correspond in higher land values compared to illiterate farm workers. Household size was used as a proxy for labor and the result is not surprising that an addition of labor in the farm increases the farmland values by 25.6%. The significance of the age coefficient suggests that more mature workers are willing to work harder in the fields and it results in higher farm land values through higher crop productivity. Household farm size is positive and significant for irrigated and dry land farms and the results should not be startling. The beta coefficients reveal that the farmland values were higher for irrigated farms (18.8 standard deviation increase v/s 8 standard deviation increase) when farm size increases. Credit amount is positive and significant for irrigated farmlands but not for dry land farms. A 1 unit increase in credit amount led to an increase of farm land values in irrigated farms by 0.2%. This result implies that access to more loans gives farm land workers greater opportunity to invest in irrigation products that further enhances their land and thus the farmland value ultimately increases.

4.6 Conclusion and policy implications

This paper used an application of the Ricardian approach to demonstrate the impact of climate and socio-economic variables on the farmland values for dry land and irrigated lands. Taking into account the major criticism of Ricardian approach that it fails to take into account the endogeneity of irrigation choices (Schlenker et al. 2005), this paper used a Heckman sample selection model to control for irrigation choices. The results indicate that Nepalese farmlands are sensitive to climate change. Irrigated farmlands were found to have a higher land value when the temperature and rainfall increased during summer season. Dry lands, on the other hand had a reduction in land value due to an increase in temperature and rainfall during spring season. This result indicates that irrigated farmlands can be an effective mechanism to protect land values against rainfall and temperature.

Similarly, it was found that all farmlands in Nepal were negatively affected by climate change during the winter and spring season. However, the impacts of climate change on land values were significantly less for irrigated farms than for dry land farms. This result further strengthens the claim that irrigation can be a great instrument for farmlands to tackle the problem of climate change. The results for the marginal impacts revealed that higher rainfall in the summer, spring and fall were associated with higher land values for irrigated farmlands. Agricultural production is one of the major mean of livelihood for most of the people in Nepal and as such, policies should be directed towards developing additional irrigation systems throughout the country. Similarly, since Nepal is a poor country, policymakers should make sure that irrigation systems are provided to households at minimal costs. Given the significance of irrigation in combating the problems of climate change, policymakers should provide education and awareness to farmers on the importance of employing irrigation as a way to increase their crop yields and boost land values.

Although this paper quantified the economic impacts of climate change on farmland values in Nepal, this study has to be strengthened furthermore. The data for the soil variable has been divided into three quality in this paper, but a better study would be to collect the soil data with a program like ArcGIS and include all types of soil available in the country. Most of the papers on Ricardian approach uses hydrological discharge rate and it has been shown to have a big influence on farmland values. This variable has not been used in this paper due to the lack of data availability and the results presented here may have been even more solid by including river discharge. Similarly, this study looks at only 36 of the 75 districts in Nepal, and so the results should be more precise if climate data for the entire country is used to reassess the significance of climate change on the three different belts in Nepal: Hilly, Terai and Mountain.

4.7 Figure and Tables

Table(4.1) : Descriptive statistics of the major variables in the study

Variable name	**Variable label**
irr_choose	Choice of irrigation (1 = irrigated farms ; 0 = dry land farms)
Log land Value	Monetary value of the farmland (Rs) in logarithm form
Precipitation winter	Mean (standardized) total winter rainfall 1971-2008
Precipitation sq. winter	Square of winter mean precipitation
Temperature winter	Mean (standardized) total winter temperature 1971-2008
Temperature sq. winter	Square of winter mean temperature
Precipitation summer	Mean total (standardized) summer rainfall 1971-2008
Precipitation sq. summer	Square of mean precipitation
Temperature summer	Mean total (standardized) summer temperature 1971-2008
Temperature sq. summer	Square of mean summer temperature
Precipitation spring	Mean total (standardized) spring rainfall 1971-2008
Precipitation sq. spring	Square of mean spring precipitation
Temperature spring	Mean (standardized) total spring temperature 1971-2008
Temperature sq. spring	Square of mean spring temperature
Precipitation fall	Mean (standardized) total fall rainfall 1971-2008
Precipitation sq. fall	Square of mean fall precipitation
Temperature fall	Mean (standardized) total fall temperature 1971-2008
Temperature sq. fall	Square of mean fall temperature
Credit amount	Total loan taken for inputs and farm use
HH_farmsize	Total plots owned by household (ropani)
Distance to input market	Km distance to the nearest agricultural center
Age	Age of household head
Gender	Sex of household head (1 = Male ; 0 = Female)
Log HHsize	Log of household size
Electricity	Availability of electricity in the household (1 = yes ; 0 = No)
Education	Education of the household head (1 = literate ; 0 = illiterate)
Log Elevation	Log of the elevation level of farmlands
Domsoil	Soil quality of the farmland (1 = bad ; 2 = moderate ; 3 = good)

Table (4.2): Selection Model (Probit)

VARIABLES	Irrigation (1/0)
Precipitation Winter	-0.603*
	(0.349)
Temperature Winter	-0.251
	(0.297)
Precipitation Summer	0.791***
	(0.196)
Temperature Summer	0.581***
	(0.184)
Precipitation Spring	0.576
	(0.435)
Temperature Spring	-0.728**
	(0.324)
Precipitation Fall	0.715*
	(0.406)
Temperature Fall	-0.373
	(0.329)
2. soil (Moderate quality)	0.787***
	(0.148)
3.domsoil (Good quality)	0.551***
	(0.110)
Constant	-0.263
	(0.176)
Observations	1,165

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table(4.3) Land value regressions

	Irrigated	Dryland
	(1)	(2)
VARIABLES	Landvalue	Landvalue
Precipitation Winter	-5.008	-1.739
	(-0.365)	(-0.127)
Precipitation Sq Winter	-0.435	-9.539**
	(-0.0101)	(-0.218)
Temperature Winter	-8.429**	-7.321*
	(-1.508)	(-1.113)
Temperature Sq Winter	6.164**	6.314**
	(1.327)	(1.277)
Precipitation Summer	11.68*	2.785
	(1.795)	(0.451)
Precipitation Sq Summer	-1.517	-0.450
	(-0.126)	(-0.0459)
Temperature Summer	6.670*	0.626
	(1.526)	(0.140)
Temperature Sq Summer	-3.726**	-5.227***
	(-0.467)	(-0.737)
Precipitation Spring	10.94*	4.259
	(0.966)	(0.358)
Precipitation Sq Spring	-32.92***	-22.18***
	(-0.707)	(-0.424)
Temperature Spring	-11.49*	-28.18***
	(-1.868)	(-3.553)
Temperature Sq Spring	-10.65**	-24.13***
	(-1.587)	(-3.168)
Precipitation Fall	7.414*	2.574
	(0.699)	(0.255)
Precipitation Sq Fall	10.39	34.41***
	(0.168)	(0.608)
Temeprature Fall	-8.813	-30.82***
	(-1.204)	(-3.700)
Temperature Sq Fall	4.296	21.69***
	(0.629)	(3.154)
Credit Amount	0.00264***	-0.000254
	(0.153)	(-0.0211)
HH Farmsize	0.0112***	0.00807**
	(0.188)	(0.0804)
Electricity (1/0)	0.709***	0.989***
	(0.174)	(0.275)
Age	0.00768*	0.00802
	(0.0648)	(0.0598)
Gender	0.197	-0.167
	(0.0565)	(-0.0440)
Education (1/0)	0.489***	0.211
	(0.131)	(0.0496)
Log HHsize	0.256**	0.192

	(0.0773)	(0.0545)
Distance to input market	-0.0252***	-0.033***
	(-0.122)	(-0.162)
Log elevation	-0.0246*	-0.0291*
	(-0.119)	(-0.136)
2.domsoil (Moderate)	10.77*	-0.237
	(3.384)	(-0.0587)
3.domsoil (Good)	6.274*	-1.298
	(2.011)	(-0.380)
imr	22.78*	0.348
	(3.348)	(0.0509)
Constant	-5.690	17.50
Observations	573	573
R-squared	0.334	0.304

Robust normalized beta coefficients in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table (4.4): Marginal precipitation coefficients (Irrigated Farms)

	ey/dx	Delta-method Std. Err.	z	P>z	[95% Conf.	Interval]
Precipitation winter	-0.394309	0.3058092	-1.29	0.197	-0.9936841	0.2050661
Precipitation summer	0.91971	0.478057	1.92	0.054	-0.0172646	1.856685
Precipitation spring	0.8614603	0.4629482	1.86	0.063	-0.0459016	1.768822
Precipitation fall	0.5837569	0.3027381	1.93	0.054	-0.0095988	1.177113

Table (4.5): Marginal temperature coefficients (Irrigated Farms)

	ey/dx	Delta-method Std. Err.	z	P>z	[95% Conf.	Interval]
Temperature winter	-0.663638	0.2918445	-2.27	0.023	-1.235643	-0.091633
Temperature summer	0.5251379	0.3174809	1.65	0.098	-0.0971131	1.147389
Temperature spring	-0.9050452	0.4805529	-1.88	0.06	-1.846912	0.0368213
Temperature fall	-0.6938665	0.4960486	-1.4	0.162	-1.666104	0.2783708

Table (4.6): Marginal precipitation coefficients (Dry Land Farms)

	ey/dx	Delta-method Std. Err.	z	P>z	[95% Conf.	Interval]
Precipitation winter	-0.147874	0.3109733	-0.48	0.634	-0.7573705	0.4616225
Precipitation Summer	0.2367948	0.5157799	0.46	0.646	-0.7741152	1.247705
Precipitation Spring	0.3621471	0.4448185	0.81	0.416	-0.5096812	1.233975
Precipitation Fall	0.2188252	0.3409727	0.64	0.521	-0.4494689	0.8871194

Table (4.7): Marginal temperature coefficients (Dry Land Farms)

	ey/dx	Delta-method Std. Err.	z	P>z	[95% Conf.	Interval]
Temperature winter	-0.6224928	0.3605393	-1.73	0.084	-1.329137	0.0841512
Temperature summer	0.0532041	0.3608528	0.15	0.883	-0.6540543	0.7604625
Temperature spring	-2.396404	0.5314054	-4.51	0	-3.43794	-1.354869
Temperature fall	-2.620754	0.4930475	-5.32	0	-3.58711	-1.654399

Chapter 5: Concluding Remarks

5.1 Dissertation Summary

Our world today faces a myriad of unprecedented environmental challenges that transcends spatial and temporal reach. These problems involve interconnected ecological and social systems operating on multiple scales and includes climate disruption, water stress, food security, biodiversity loss, ozone depletion, persistent organic pollutants, over-population and species declines and extinctions. Developing nations are perhaps the biggest contributor to the global environmental problems since environmental protection is many poor nations are considered to be a luxury that only rich countries can afford. These issues are even more augmented due to the unprecedented growth the world is currently undergoing. As such, poor environmental quality is an inevitable problem of growth and development in many poor countries. As cities around the world expand, the pressure on the environment continues to amplify even more. Nepal is one such developing country that currently faces countless environmental challenge as the country undergoes rapid growth and expansion. These environmentally unsound development practices will not only affect the ecosystem functioning and dynamics, but it also threatens the future development of the country. The overall theme of this dissertation was to economically examine the consequences of environmental challenges in Nepal. Among the myriad environmental issues, I investigated three significant environmental challenges: problem related to freshwater ecosystem management and conservation, challenges with drinking water quality and availability, and issues related to climate change adaptation and mitigation.

Chapter 1 provided the motivation and some background information on the three environmental challenges. Furthermore, I also discussed the survey design procedure, data structure and highlight some relevant statistics of the survey variables. In my second chapter, I investigated the impact of urbanization on one freshwater ecosystem, the Danda River Basin, in Nepal. Danda River flows through Siddharthanagar, a rapidly urbanizing city near the Nepal-India border, situated in the fertile flat lands of the Indo-Gangetic plain. The river ecosystem constitutes a valuable natural resource in economic, cultural, aesthetic, scientific and educational terms to the people in Siddharthangar. However, the health of the river is rapidly declining in recent years due to the haphazard urbanization in the city. One byproduct of unplanned growth in the city has been the discharge of waste water and toxins from households, agricultural and industrial uses into the river. Additionally, loss of biodiversity and aquatic species, an inevitable consequence of urban growth and the deteriorating health of Danda River, is a growing concern. Likewise, many households rely on groundwater boring for water and a number of these sites are located near the river, which has exacerbated the sanitation and health problems in the city.

I used a choice experiment method to explore households' preference for the conservation of the Danda river ecosystem. The major contributions of this study are threefold. First, this paper adds to the limited number of choice experiment studies that confront the issue of sustainable management of urban river systems in developing countries and is the only one to focus on the Danda River Basin in Nepal. Second, from an empirical point of view, I use the Generalized Multinomial Logit (GMNL) model and incorporate respondents' preference uncertainty in a bid to increase the precision of the marginal willingness to pay (MWTP) estimates. Third, I explicitly account for spatial heterogeneity by employing a hot spot analysis, and as a result, deviate from the continuous distance-decay method commonly assumed in stated preference (SP) studies.

I find evidence of substantial demand for the Danda ecosystem services. The results suggest that respondents are willing to pay as much as $17.06/year for the highest quality of river water, while the MWTP to protect the riverbank to 300 feet is $3.15/year and $13.46/year to introduce vegetation in the riverbanks. The inclusion of preference uncertainty in the estimation process resulted in an improved model fit and produced tightened confidence intervals for the marginal MWTP estimates. I find a presence of statistically significant hot and cold spot pockets for different ecosystem services, indicating local spatial heterogeneity. In particular, people in the urban area seem to derive benefits from the Danda for recreational activities, while the rural population desires improvement in Danda water quality for agricultural purposes. Finally, I observe that the public prefers a community-based management of the Danda River. This finding highlights the need for policymakers to decentralize their management to achieve community participation for sustainable conservation of natural resources starting from the grassroots level.

In my third chapter, I investigated households' water averting behavior by placing a particular emphasis placed on the gap between the households' perception of their water quality levels, and the objective water quality level. Water quality remains a major concern and a serious health issue in the developing world. An effective remedy to the health issues caused by impure water quality can be in-home water treatment. Previous studies indicate that in-home water treatment can be one of the cheapest and most effective means of preventing waterborne illnesses like diarrhea and diarrheal diseases (Clasen et al., 2007a). Nonetheless, the widespread prevalence of water-related diseases in the developing world suggests that many households fail to engage in any water averting behaviors including in-home water treatment. A number of studies have attempted to explain households' water averting behaviors by taking into account how behaviors are initially formed. These studies largely underline the role of perceived risks in influencing water handling behaviors. Then there are other set of studies that place significant weight on possessing information on the water quality levels as vital to changing households' behaviors. However, so far, the literature does not combine the divergence between perception and objective water quality levels to explain water handling behavior.

My study attempts to fill the gap in the water averting literature by exploring whether the gap between perceived and actual water quality levels could influence the adoption of environmental risk-averting behavior in the form of water treatment by households. The subjective perception of the water quality level is based on the household's assessment of the safety of their water quality. The actual water quality is based on the level of *Escherichia coli* (E. coli) bacteria on the household's drinking water. I employ these two sets of data in an attempt to explore the information gap between perception and reality regarding the drinking water quality level to understand how the differences could affect a household’s decision to treat their water.

I drew data from 311 households in Siddharthanagar, Nepal to examine the water handling behaviors. The finding indicates that the gap between perception and reality does play a role in a household's decision to employ water treatment measures. Households' with a larger gap between perception and actual water quality levels were less likely to treat their water. On the other hand, households that had a minimal gap were more likely to adopt water treatment measures. This finding highlights the need to devise policies targeted towards minimizing the information gap to help households' make informed decisions and thereby reduce the outbreaks of water-borne diseases. Results also suggest that the water source, education level, and the taste of the drinking water drives the averting behavior as well.

In my fourth chapter, I explore the impact of climate change on farmland values in Nepal. The major contribution of this paper is that I incorporate the potential endogeneity concern that arises in irrigation choices. This is a problem because a farmer’s choice of irrigation can be affected by various variables, one of which is the climate itself. Thus, studies that account for this endogeneity concern can produce biased estimates. To explore the effect of climate change on farmland values, I employed a Heckman sample selection model. In the first stage, I regressed the farmland value on climate and soil variables. Using the mills ratio from the first stage, I estimated the second stage regression where by regressing farmland values on climate and socio-economic variables.

The result suggests that the impact of climate change on farmland values are significant, but the effects were different for dryland and irrigated lands. Similarly, the result also indicated that the effect of climate change on farmland values were overblown when not accounting for the endogeneity of irrigation choices. The effect of temperature changes on farmland values was more pronounced for drylands than for irrigated lands. Increase in temperature during the winter and spring season decreased farmland value in both the irrigated and the drylands, but the impact was more pronounced in the latter case. Likewise, the higher precipitation resulted in higher farmland values. However, the effect of precipitation was also more pronounced for dryland than for irrigated farmlands. This finding suggests that while climate change affects the agricultural productivity, the effects might be more severe for irrigated lands. Thus, the potential for adaptation strategies also lies in understanding the mechanisms that farmers employ to irrigate their land.

5.2 Future Research Agenda

In my future, I plan to develop my research agenda by exploring a wide array of empirical problems that lie at the nexus between humans and the environment in the urban sector. I am particularly interested in addressing issues on water policy and ecosystem services, environmental resiliency and vulnerability, built environment, climate change mitigation and adaptations, water, sanitation and hygiene programs, and human health and well-being. One overarching theme I would like to use to address these various issues is by exploring the role of local governance in the sustainable management of environmental resources.

In my second chapter, I employed the Choice Experiment method to explore household preferences for freshwater conservation. Two interesting findings from the paper include the households' preference for a community-based river ecosystem management; and the existence of local spatial heterogeneity for the different river ecosystem services. In my future research I would like to delve deeper into choice experiment method as an environmental valuation tool and explore novel ways to elicit unbiased preferences. Some of these include exploring approaches to explicitly model environmental governance in the CE model, dealing with households' that make uncertain choices, investigating the impact of discounting and time-value on preferences, integrating GIS tools understand aspects of spatial heterogeneity, and exploring non-monetary payment mechanisms (for e.g., contributing time instead of money) to explore the valuation of non-market goods and activities.

In my third chapter, I explored households' water treatment behavior by investigating the gap between the perception of their water quality and the actual quality level measured by the count of E.Coli bacteria. Results suggest that households with a minimal gap between their perception and reality were more likely to treat their water than households otherwise. Expanding on this idea, my future research interest is on developing and testing interventions to stimulate adoption of environmental health improvements. For example, it would be interesting to explore whether information provision of environmental risks and/or implementation of citizen science approaches (for e.g., by training volunteers on measuring water quality levels) could stimulate the demand for measures to improve drinking water quality.

My fourth chapter explored the impact of climate change on agricultural productivity by incorporating extreme climate events. The findings indicate that agricultural productivity in Nepal is not only affected by rainfall and temperature, but it is also sensitive to extreme climate events. Expanding on this topic, I am interested in looking at the impact of extreme climate events (climate shocks like flooding or drought) on community resiliency and vulnerability. Some of the questions to explore within this framework include: Are households that are more resilient able to recover quickly from extreme climatic events or not? What is the role of social capital and networks in helping communities bounce back from natural disasters and environmental catastrophes? How does governance help in the recovery? What role does risk perception and tolerance level play in households' climate mitigation strategies? How do community livelihoods (e.g., food security and poverty), socio-economic conditions (e.g., demographic dynamics), risk, perception and understanding of future climate impact, coping strategies, and cultural practices?

5.2.1 Longer Term Research Plan:

On a more longer-term horizon, I am interested in employing the ideas discussed above to undertake a project to understand the coupled dynamics between the human and the urban ecological systems. I am particularly interested in exploring the feedback and linkages by which humans influence and are in return themselves affected by the natural patterns and processes.

Going back to my dissertation, two chapters of my thesis are a case study on the environmental issues caused by haphazard urbanization in the town of Siddharthanagar, Nepal. Variations in climate and changes in land use patterns through urbanization in Siddharthanagar are likely to have significant impacts on ecosystem structure, functions and dynamics as a whole. A natural question to investigate would be to explore how this city and its surrounding landscape will change in the next 20 years in response to climate change and its effect on the surface and ground water conditions. The exposure, vulnerability and impacts of climate change and urbanization will have direct and indirect influence on the livelihood of people through various systems such as water, human settlements, tourism, property values and human health. For instance, urbanization will most likely result in land-use and land cover changes which affects the biotic and abiotic ecosystem, causes micro-climatic changes and also results in surface and ground water stress and increased pollution in the city. The outome of such environmental transformations will ultimately affect social and economic organizations in the form of price hikes in the real estate market, health of the residents residing there, quality of life, eco-tourism on which the city is dependent upon, urban infrastructures, and perhaps the general social network structure in the city.

My research plan for the longer-term is to understand how we can model these kinds complex of interactions between humans and the urban-environment so that we can make the urban communities more resilient to environmental catastrophes. Some other questions I would like to explore in this framework include questions like: Is there a critical threshold beyond which the anthropogenic impacts on the urban ecology become permanent? How do the societal time preference (i.e., the social discount rate) affect the sustainability of human development scenarios? How do the feedback mechanisms differ across spatial and temporal scale? How can we design governance mechanisms (i.e., local v/s global and centralized v/s decentralized) and what roles do institutions play in making urban communities more resilient in the face of ecological vulnerabilities that we create? This kind of study would allow me to design policies to build community resiliency, understand adaptation strategies, close the knowledge gap of the community so they can better deal with such problems, and ultimately these results would also be transferable to other locations with similar characteristics.

APPENDIX A: Survey Questionnaire

Danda River Management Practices, Environmental Pollution, Household Water Quality and Health Risks: A Knowledge, Attitude, Behavior and Choice Experiment Survey.

Namaskar, my name is ………….. from the Nepal Study Center at the University of New Mexico, USA. We are conducting a survey with the residents of Bhairahawa to understand their opinions on river ecosystem, environmental pollution and household water quality. The main objective of this survey is to collect information on environmental quality, especially river water quality in Danda. Along with that, we will also gather information on household drinking water practices, and pollution problems in Bhairahawa. *The information obtained will allow us understand the potential for ecosystem improvements in Danda River, how much people value a clean Danda River, and also the health risks associated with environmental pollution and water treatment behavior among households.* Your views will help policymakers to make informed decisions on these issues. Most of the questions are regarding your opinions, so there is no right or wrong answers. Participation is voluntary and you can quit this interview any time you want. Your answers to these questions are completely confidential and the data will not be used in any way to identify you personally.

Thank you very much for your kind co-operation.

To be filled by enumerators.

Note to enumerators: Please write number in English

<table>
<tr><td colspan="4">SURVEY VERSION:__</td></tr>
<tr><td colspan="2">PSU Code:</td><td colspan="2" rowspan="2">Date of Interview:
(day/month/year) eg. 30 March 2016</td></tr>
<tr><td colspan="2">HH NO:</td></tr>
<tr><td colspan="4">Household Latitude:</td></tr>
<tr><td colspan="4">Household Longitude:</td></tr>
<tr><td colspan="4">Respondent's Name:</td></tr>
<tr><td colspan="4">Phone Number:</td></tr>
<tr><td colspan="2">Respondent's Age:</td><td colspan="2" rowspan="2">Respondent's signature:</td></tr>
<tr><td colspan="2">:</td></tr>
<tr><td>Location</td><td>Siddharthanagar ☐</td><td>Basantapur ☐</td><td>Bagaha ☐</td></tr>
<tr><td colspan="2">Ward Number:</td><td colspan="2">Enumerator's name:</td></tr>
<tr><td colspan="2">Tole name:</td><td colspan="2">Enumerator's code:</td></tr>
<tr><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td colspan="2">Begin Time:</td><td colspan="2" rowspan="2">Signature:</td></tr>
<tr><td colspan="2">End Time:</td></tr>
</table>

Part 1: Environmental Knowledge, Attitude and Concern

1. How important are the following factors to you and your family?

		1 = Not Important	2 = Somewhat Important	3 = Very Important	4 = Don't Know
i.	Peace and Security				
ii.	Environment				
iii.	Economic Development				
iv.	Protection of Nepal's cultural and social heritage				
v.	Danda River's protection				

2. Given the following list of environmental issues, please indicate how serious these factors are to your community.

		1 = Not Important	2 = Somewhat Important	3 = Very Important	4 = Don't Know
i.	Water Pollution				
ii.	Air Pollution				
iii.	Traffic Congestion				
iv.	Household waste				

3. Some people believe that controlling water pollution in Danda River is really important, while others feel that there is no problem in Danda River. Do you think that Danda River should be cleaned?

1 = Yes	2 = No

		1 = Yes	2 = N0	3 = Don't Know
i.	Fertilizers and pesticides are harmful because they cause algae to grow, which destroys water plants			
ii.	Polluted water carries diseases			
iii.	Which of the following diseases or health conditions is caused by the ingestion of water contaminated with pathogenic bacteria, viruses, or parasites?			
	a. Cancer			
	b. Diarrhea			
	c. Diabetes			
iv.	Have you heard of the bacteria called E.coli			

4. Please answer the following question based on what you know.

5. In your opinion, how likely do you think:

		1 = Not at all likely	2 = Somewhat likely	3 = Very likely	4 = Don't know
i.	Bathing in the Danda river on a regular basis will cause health problems?				
ii.	Drinking a few drops of water from the Danda river will cause health problems?				
iii.	Washing clothes in the Danda River on a regular basis will cause health problems?				
iv.	Walking along or across the Danda river on a regular basis will cause health problems?				
v.	Pollution from the Danda River adversely affects agriculture?				

6. **How do you think that your households would benefit if Danda River was improved?** *(Check either benefit or no benefit for all the categories.)*

		1 = Benefit	2 = No Benefit
i.	Agriculture		

ii.	Fishery		
iii.	Better health		
iv.	Recreation (Swimming, Boating, aesthetic pleasure etc.)		
v.	Improved quality of drinking water supply		
vi.	Increase in the price of house/lands		
vii.	Cultural and religious activities		

7. In your opinion, how much money should be spent on improving the quality of Danda River? *(Please check one)*

1 = Much more than currently being spent	2 = Little more than currently being spent	3 = Money should not be spent in Danda River	4 = Don't Know

8. What would you be willing to do to improve the quality of Danda River? *(Please check one)*

1 = Pay more money	2 = Volunteer in cleanup program	3 = Attend meetings and talks with neighbors about clean-up programs	4 = Join local water conservation groups

9. Danda River can be restored to a better state if everyone in the community volunteered in cleanup program for few hours a week. How many hours would you be willing to volunteer per week to restore Danda River?
_________________ hours per week

Part 2: Choice Experiment

Note to the enumerators: Please read everything in this section to the respondents

The Danda River is an important River running through the heart of Bhairahawa. However, for the past several years, the quality in and around Danda River has continually been degrading as a result of runoffs from industrial and agricultural uses, household sewage disposals and unplanned waste management system.

10. **In your opinion, how important are these factors in causing pollution in Danda River?**

		1 = Less Important	2 = Somewhat Important	3 = Very Important	4 = Don't Know
i.	Household Sewage				
ii.	Discharge from hospitals and hotels				
iii.	Industrial waste discharge				
iv.	Agricultural waste water				
v.	Human waste (urine or defecation)				

There are many recommendations that have been proposed for better management of the Danda River Basin. Among those, we have selected 6 important attributes:

1. River water quality
2. River bank protection
3. Tree plantation along the riverbanks
4. River monitoring and educational program
5. Management fee
6. Regulatory mechanism

Now, I would like to talk to you in some more details about the 6 recommendations that have been proposed for the management of Danda River Basin.

1. **River water quality**

The river water quality in this project could be improved to three possible levels:

a) **Boatable:** The River could be cleaned to a point where it is suitable for boating in the water. In order to achieve this, there will be a substantial improvement in color and odor of water. However, at this stage, the water will not be suitable for human contact or fish and other aquatic animals to survive.

11. **How supportive are you of cleaning the water of Danda to the level where it is possible for boating?**

1 = Not supportive	2 = Somewhat supportive	3 = Very supportive	4 = Don’t Know

b) **Boatable, and suitable for fishing:** The River will be cleaned to a point where fishes and other aquatic animals can survive in the water. At this point, it is possible not only to boat, but also to fish in Danda River.

12. **How supportive are you of cleaning the water of Danda to the level where it is possible for boating and fishing?**

1 = Not supportive	2 = Somewhat supportive	3 = Very supportive	4 = Don’t Know

c) **Suitable for boating, fishing and for irrigation:** The River will be cleaned to a point where it is possible for the river water to be used for irrigation as well. This state will be achieved by removing pathogens from water that could harm plants.

13. **How supportive are you of cleaning the water of Danda to the level where it is suitable for boating, fishing and for irrigation?**

1 = Not supportive	2 = Somewhat supportive	3 = Very supportive	4 = Don’t Know

14. **Which option do you think is more suitable and practical for Danda River?**

1.	Boatable
2.	Boatable and swimmable
3.	suitable for boating, fishing and irrigation
4.	Others: ____________

2. **River bank protection**

The haphazard urbanization in Bhairahawa has resulted in uncontrolled growth of informal settlements and consequently the riverbanks in Danda basin are being occupied. Such activities threaten the ecosystem of the river, hence the government recently made 50 feet zone on riverbanks an off-limit area for urban encroachment (no homes, no businesses etc.).However, studies show that riverbanks need at least 150 - 300 feet protection to maintain a healthy ecosystem.

15. **How supportive are you of increasing the river bank off limit zone from 50 feet to 150 feet?**

1 = Not supportive	2 = Somewhat supportive	3 = Very supportive	4 = Don't Know

3. **Riverside tree plantation**

We are proposing to plant trees along the banks of Danda. Planting trees will not only stabilize the river bank, it will also improve water cleanliness, enhance biodiversity and also boost the visual image of this city. Right now, only about 10% of the banks have trees.

16. **How supportive are you of increasing the share of riverbanks having trees from 10% to 80%?**

1 = Not supportive	2 = Somewhat supportive	3 = Very supportive	4 = Don't Know

17. **Which option do you think is more suitable and practical for Danda River?**

1.	10% of the riverbanks covered with trees
2.	40% of the riverbanks covered with trees
3.	80% of the riverbanks covered with trees
4.	Other:______________

4. **River monitoring and educational program**

We plan to create a platform for community to exchange educational, cultural and research information that is derived from the River ecosystem. This will be done by implementing a river monitoring and educational program in the Danda basin. River monitoring will be done through regular testing of river water, while educational program includes field visits by children from various schools to learn about river ecology and nature.

18. **How important do you consider it is to have a monitoring program in Danda River?**

1 = Not Important	2 = Somewhat Important	3 = Very Important	4 = Don’t Know

5. **Cost of the program**

The financial structure and source of financing are crucial for the implementation of this project. By itself, the government cannot cover the full cost. As such, residents may need to contribute some amount for the Danda river restoration program. The project will partially be funded by the government, and the remaining fund needs to be collected from the residents of Siddharthanagar, Bagaha and Basantapur. To obtain this funding, you will be charged with an annual “Danda River management fee” in your local municipal tax for a period of 5 years.

19. If Danda river management program were to be implemented by introducing the attributes proposed above, how much would you be willing to pay per year to support such program?
    Rs. _________________

6. **Regulatory Mechanism**

People sometime have different preference over who handles the collected funds. There are different projects in Nepal with varying mechanisms for fund collection. For e.g., solid waste management is primarily undertaken by municipality, while forest management in many parts of the country is done by the community. We have proposed 3 regulatory mechanisms for Danda River.

1. Community: A community trust fund will be created to manage the collected funds.
2. Government: A central government body will manage and administer the collected funds.
3. Municipality: The collected funds will be managed by the municipality.

20. Who would you prefer to handle the collected funds for Danda River management?

1.	Community
2.	Municipality
3.	Government
4.	Other (Please specify): ________________

Which River management plan do you prefer?

Note to enumerators: *Please show the tables to the respondents while asking to choose the river management packages.*

On the next page, you are given three different Danda ecosystem management plans: Management plan A, Management plan B and Current Management Plan.

- Among the three plans, please choose the one that you prefer. These plans contain the recommendations for Danda management system mixed into different levels.

- If you are satisfied with the current situation of Danda River, you can choose Investment plan C "Status Quo", which is the current situation of the river ecosystem and costs you no money.

- If none of the options exactly matches your expectations, please choose the one that you dislike the least.

- While choosing your answer, please consider benefits of the proposed program and your net income since the packages have different fees associated with them.

- There are many sets of management plans. We will show you three sets of plans and each time ask you which one you prefer. This is to ensure that we get an accurate reflection of your choice. Please do not mind answering similar table 3 times.

1. *Suppose plans A, B and C are the only ones available*					
	Management Plan A		**Management Plan B**		**Current Management Plan "Status Quo - C"**
River Water Quality	Water will be **suitable for boating and fishing**.		The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**		The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**
River bank protection	**150 feet** on both sides		**300 feet** on both sides		**50 feet** on both sides
Tree Plantation	**10%** of the banks will be planted with trees		**80%** of the banks will be planted with trees		Currently **10%** of the banks are planted with trees.
River monitoring and educational program	**No** monitoring and educational program		**There will be** a monitoring and educational program.		Not applicable
Management fees	Rs. 1800/year (for 5 years)		Rs. 125/year (for 5 years)		Rs.0
Regulatory mechanism	Municipality		Community		Currently not available
Which package do you prefer (choose one only)	**I choose plan A ☐**		**I choose plan B ☐**		**I choose 'current situation' plan C ☐**

21. (I) How certain are you of your choice?

1= Very uncertain	2= Somewhat uncertain	3 = Neither certain nor uncertain	4 = Somewhat certain	5 = Very certain

2. *Suppose again plans A, B and C are the only ones available*					
	Management plan A		**Management Plan B**		**Current Management Plan "Status Quo - C"**
River Water Quality	Water will be **suitable for boating, fishing and for irrigation**.		The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**		The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**
River bank protection	**50 feet** on both sides		**300 feet** on both sides		**50 feet** on both sides
Tree Plantation	**80%** of the banks will be planted with trees		**40%** of the banks will be planted with trees		Currently **10%** of the banks are planted with trees.
River monitoring and educational program	**No** monitoring and educational program		**There will be** a monitoring and educational program.		Not Applicable
Management fees	Rs. 3500/year (for 5 years)		Rs. 1800/year (for 5 years)		Rs.0
Regulatory mechanism	Municipality		Community		Currently not available
Which package do you prefer (choose one only)	**I choose plan A ☐**		**I choose plan B ☐**		**I choose 'current situation' plan C ☐**

21. (II) How certain are you of your choice?

3. ***Suppose again plans A, B and C are the only ones available***			
	Management Plan A	**Management Plan B**	**Current Management Plan "Status Quo"**
River Water Quality	Water will be **suitable for boating, fishing and for irrigation**.	The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**	The water is full of algae and it emits foul odor. **Not suitable for boating, fishing or for irrigation.**
River bank protection	**150 feet** on both sides	**50 feet** on both sides	**50 feet** on both sides
Tree Plantation	**40%** of the banks will be planted with trees	**80%** of the banks will be planted with trees	Currently **10%** of the banks are planted with trees.
River monitoring and educational program	**No** monitoring and educational program	**There will be** a monitoring and educational program.	Not applicable
Management fees	Rs. 10/year (for 5 years)	Rs. 3500/year (for 5 years)	Rs.0
Regulatory mechanism	Government	Municipality	Currently not available
Which package do you prefer (choose one only)	**I choose plan A ☐**	**I choose plan B ☐**	**I choose 'current situation' plan C ☐**

1= Very uncertain	2= Somewhat uncertain	3 = Neither certain nor uncertain	4 = Somewhat certain	5 = Very certain

21. (III) How certain are you of your choice?

1= Very uncertain	2= Somewhat uncertain	3 = Neither certain nor uncertain	4 = Somewhat certain	5 = Very certain

22. While making your choice, how important was the following attributes in choosing the service packets?

		1 = Less Important	3 = Somewhat Important	3 = Very Important	4 = Don't Know
i.	How important was river water quality in your choice?				
ii.	How important was riverbank protection in your choice?				
iii.	How important was tree plantation in your choice?				
iv.	How important was river monitoring and educational program in your choice?				
v.	How important was the management fee in your choice?				
vi.	How important was regulatory mechanism in your choice?				

23. *(Ask if they chose status quo, 'C').* Why did you choose the status quo, 'X' instead of the other alternatives?

1.	Yearly user fee was too high
2.	Do not consider Danda river management to be an important issue
3.	It is the responsibility of the government
4.	I am satisfied with the status quo
5.	Other reason: ________________

Part 3: Household drinking water source and treatment behavior

24. What is the main source of drinking-water for members of your household? (please select one)

1. Piped water into dwelling
2. Public tap/ standpipe
3. Tubewell / borehole
4. Boring water
5. Well water
6. Protected spring
7. Unprotected spring
8. Rainwater collection
9. Bottled water
10. Cart with small tank/drum
11. Tanker-truck
12. Surface water (river, dam, lake, pond, stream, canal, irrigation channels)
13. Others (Specify): _________________

25. How long does it take to go there, collect water, and come back?

1.	Water on premises
2.	Number of Munites : _______________ (If water is not on premise)
3.	Don't know

26. How often do you wash the utensils where you save your drinking water?

1= Once a day	2= Once every 2-3 days	3 = Once a week	4 = Once a month	5 = Never

27. Do you treat water in any way to make it safer to drink? (If no, go to # 29)

1. Yes
2. No
3. Don't know

28. What do you usually do to the water to make it safer to drink?

1.	Boil
2.	Add piyush chlorine/ bleach
3.	Strain it through a cloth
4.	Use a water filter (ceramic, sand, composite, etc.)
5.	Use euroguard
6.	Solar disinfection
7.	Let it stand and settle
8.	Don't Know
9.	Others (Specify): ____________________

29. How would you judge the safety of the water from your main source of drinking water, before applying any treatment?

1.	No risk
2.	Little risk
3.	Some risk
4.	Serious risk
5.	Don't know

30. In your opinion, how do people in this ward judge the safety of the water from your main drinking source before applying any treatment?

1.	No risk
2.	Little risk
3.	Some risk
4.	Serious risk
5.	Don't know

31. Perceptions of drinking water quality:

		1 = Yes	2 = No	3 = Don't Know
i.	I am satisfied with the taste of drinking water in my house			
ii.	I am satisfied with the color of drinking water in my house			
iii.	I am satisfied with the odor of drinking water in my house			
iv.	Some friends and/or family told me negative comments regarding water in this community			
v.	My drinking water (before treatment) is contaminated with lead			
vi.	My drinking water (before treatment) has too much chlorine			
vii.	My drinking water (before treatment) is contaminated with Arsenic			
viii.	My drinking water (before treatment) has coliform			
ix.	My drinking water (before treatment) contains different kinds of bacteria			

32. Health knowledge: Which of the following do you think are causes of diarrhea disease?

		1 = Yes	2 = No	3 = Don't Know
i.	Eating more food			
ii.	Infection from viruses, bacteria and worms			
iii.	Eating in restaurant			
iv.	Poor sanitation			
v.	Religious belief			
vi.	Polluted air			
vii.	Contaminated water			
viii.	Poor nutrition			

33. Which of the following would you say are ways of preventing diarrhea disease?

i.	Filtering or boiling drinking water
ii.	Washing hands after using latrine
iii.	Good nutrition
iv.	Don't know: ________________

Part 4: Pollution Perception and Problems

34. How strongly do you feel you are affected by air pollution in your residential area?

1= Not at all affected	2= Slightly affected	3 = Moderately affected	4 = Strongly affected	5 = Very Strongly affected

35. How strongly do you feel you are affected by noise pollution in your residential area?

1= Not at all affected	2= Slightly affected	3 = Moderately affected	4 = Strongly affected	5 = Very Strongly affected

36. When you are at home, how annoyed are you by the road traffic?

1= Not annoyed	2= Slightly annoyed	3 = Moderately annoyed	4 = Very annoyed	5 = Extremely annoyed

37. On a 10-point scale, where "1" means completely polluted and "10" means completely clean, and 5 being halfway in between, how would you rate the water quality of the streams and rivers in your area?

1	2	3	4	5	6	7	8	9	10

38. In the past few years, would you say that you have personally made significant changes, some changes, or no changes in your activities, specifically to protect the water quality in local streams and/or the Danda River?

1= Significant changes	2= Some changes	3 = No changes

39. Where does the household wastewater (waste from kitchen, shower, cleaning etc.) go to?

i.	Directly to Danda River
ii.	To streams or river channel
iii.	Open land or pit hole
iv.	Vegetable garden (karesa bari)
v.	Wastewater network
vi.	Don't know
vii.	Others (specify):________________

40. What kind of toilet facilities does your household usually use? (If flush or pour flush: Where does it flush to?)

i.	Flush/pour flush to:
	1. Piped water system
	2. Septic tank
	3. Pit latrine
	4. Elsewhere
	5. Unknown place/not sure/ Don't know where
ii.	Ventilated improved pit
iii.	Pit latrine with slab
iv.	Pit latrine without slab/ Open pit
v.	Composting toilet

vi.	Bucket
vii.	Hanging toilet/hanging latrine
viii.	Bush or field
ix.	Other (specify) ……………………

41. How often do you wash your hands with soap after using the toilet?

6= Every time	7= Most of the time	8 = Some time	9 = Never

42. How is solid waste disposed in your household?

		1 = Yes	2 = No
i.	Collected and buried		
ii.	Collected and burnt		
iii.	Kept on roadside to be collected by municipality		
iv.	Composting		
v.	Thrown onto a vacant lot or public park		
vi.	Thrown in Danda River		
vii.	Thrown in the river or nearby channels		
viii.	Others (Specify):		

43. During the last 30 days, did you and/or your family members get sick with the following disease?

44. Due to the above mentioned disease, how many days did you miss work or school in the last 30 days?

	1 = Days of school missed	2 = Days of work missed	3 = Days of personal work missed
Total Days			

45. From a range between 0 – 10, with 0 being completely dissatisfied and 10 being completely satisfied, and 5 being halfway in between, how satisfied are you with your life, all things considered?

0	1	2	3	4	5	6	7	8	9	10

	1 = Got sick	2 = Did not get sick	c= Number of sick children (0-18 years)	d= Number of sick adults (18+ year)
1. Diarrhea/Dysentery				
2. Jaundice				
3. Typhoid fever				
4. Worms				
5. Cholera				
6. Dust allergy				
7. Nausea, itchy eyes, headache				
8. Breathing problem, shortness of breath				
9. Respiratory infection				
10. Asthma				

46. From a range between 0 – 10, with 0 being completely dissatisfied and 10 being completely satisfied, and 5 being halfway in between, how would you rate your current health status?

0	1	2	3	4	5	6	7	8	9	10

47. How long does it take you to reach the following places by walking? <u>(If household is adjacent to these places, write zero minutes)</u>

	1 = minute	2 = hour
1. Unpaved road (Motor vehicles cannot pass)		
2. Paved road (Motor vehicle can pass)		
3. Danda River		
4. Nearest stream or river channel		
5. Nearest hospital or clinic		
6. Nearest Bank		
7. Nearest school		

48. Are you a farmer or do you own any agriculture land? (If no, skip to question # 53)

1. Yes
2. No

49. If you own an agricultural land, what is the mode of irrigation used?

i.	Tubewell/Boring
ii.	Canal
iii.	Danda River
iv.	Pond/lake
v.	Mixed
vi.	Other natural sources

50. Did you use any pesticides in your farms in the last year?

1. Yes
2. No

51. Did you use any fertilizers in your farms in the last year?

1. Yes
2. No

52. Where does the agricultural waste water (from irrigation, pesticides, sediments, fertilizer use etc.) go to?

i.	Directly to Danda River
ii.	To streams of river channel
iii.	Open land or pit hole
iv.	Vegetable garden (karesa bari)
v.	sewage
vi.	Kholsa
vii.	Don't know
viii.	Others (specify):________________

53. Scientists are predicting that climate change will have severe negative impact on water resources. Climate change in area like Bhairahawa is predicted to appear in the form of increasing temperature, declining rainfall, drought etc. These events will result in lower level of both groundwater and surface water. Declining level of water means less water for irrigation and drinking.

A solution to the above problem is to save water resources for future use. There are different methods for saving water. One method that is being proposed is to increase price of water so that current water consumption will decrease. Authorities will charge you an annual fee that will be included in the land tax (मालपोत). Even if you don't own a land, you have to pay this amount since you use water for your drinking purpose.

If the authority decides to collect money from the above mentioned method, how much will you be willing to pay for the program?

_______________Rs

54. How certain are you of your choice?

1= Very certain	2= Somewhat certain	3 = Neither certain nor uncertain	4 = Somewhat uncertain	5 = Very uncertain

55. If you answered Rs.0 to questions 53, what is the main reason? (Check one)

1. I don't believe that my water supply is threatened by climate change
2. I can't afford anything at this time
3. I am opposed to any fee and shouldn't have to pay more to ensure my water supply
4. I don't believe that my money would be effectively managed by the government
5. I need more information before committing my money
6. I think there are other more important projects that the government should be focused on completing
7. Although I would be willing to support some increased fee, I'm concerned that others would not be able to afford it
8. Other (Specify):

Part 5: Socioeconomic Characteristics of the Household

❖ In this last section, I would like to ask you some questions about you and your household. This will help us understand why respondents' opinion may differ.

56. What is your completed age? …………… years

57. What is your gender (respondent)

1.	Male
2.	Female

58. Caste/ethnicity of the household head

1.	Brahman	2.	Madhesi

3.	Chhetri	4.	Madhesi Dalit
5.	Newar	6.	Pahadi Dalit
7.	Janajati	8.	Other (Please specify) : -------------------------

59. Marital Status:

1.	Never married
2.	Married
3.	Divorced
4.	Separated
5.	Widow/ Widower
6.	Living Relationship

60. How many years have you been living in this community?

1.	Less than 1 year
2.	1-5 years
3.	5-10 years
4.	More than 10 years

61. Number of members in your household (currently living in the household). *(Please write the number)*

i.	Number of children	1. 0-5 years	___________
		2. 6 – 18 years	___________
ii.	Number of adults (older than 18 years)	___________	
iii.	Number of adult with earnings	___________	

62. What is your level of education?

1.	Less than 10 complete	Number of years: ---------------------
2.	SLC complete	
3.	11 class complete	
4.	12 class complete	
5.	Bachelors (BA) complete	

6.	Masters (MA) complete
7.	Vocational training
8.	Can't read and write
9.	Can read and write
10.	Other: ____________

63. What is the occupation of the household head?

1.	Education (school, institute, university, tuition center)
2.	Government administration (administrative, bureaucratic, corporation, politics)
3.	Health (doctor, nurse, midwife, pharmacist, therapist)
4.	Information technology
5.	Business
6.	Employment (salary)
7.	Daily labor
8.	Unemployed (looking for job)
9.	Housewife
10.	Student
11.	Farmer
12.	Others (Please specify) : __________________

64. Does your household own any of these following items?

	Items	1 = Yes	2 = No	C = How many? *(If Yes only)*
1.	Radio / Tape/ CD player			
2.	Bicycle			
3.	Motorcycle / scooter			
4.	Fans			
5.	AC (Air Conditioner)			
6.	Television/deck			
7.	Telephone set/ cordless phone/ mobile phone/ pager			
8.	Sewing machine			
9.	Camera (still/movie)			
10.	Motor vehicle			

11.	Refrigerator or freezer			
12.	Washing machine			
13.	Computer			
14.	Motor Garage			
15.	Inverter or solar for electricity			
16.	Does your house have a garden?			
17.	Do you have windows in every room in your house?			
18.	Do you have alternative source of water (like tubewell/dugwell) inside your house compound?			
19.	Do you have an attach bathroom in your house?			
20.	How many bedrooms are there in this house?	____________		

65. Please indicate the range of your monthly household income. This income includes salary of all household members and income from other sources such as agriculture, business, investment and savings.

1.	Less than 5,000
2.	5,001 – 10,000
3.	10,001 – 20,000
4.	20,001 – 35,000
5.	35,001 – 50,000
6.	50,001 – 75,000
7.	75,001 – 100,000
8.	More than 100,000
9.	Do not know
10.	Decline to answer

66. Do you own this house or is this a rental house?

1.	Rental house	**Question # 67**
2.	Own the house	**Question # 68**

67. **(Only if rental house):** What is the monthly rent in this house?

	ii.

1. Rs.____________	2. Room ☐	3. Flat ☐

68. **<u>(Only if they own the house):</u>** If you were to give one flat of this house for rent, how much rent do you think you could get per month?

	ii.	
1. Rs.____________	2. Room ☐	3. Flat ☐

69. **<u>(Only if they own the house):</u>** If you were to give the whole house for rent, how much rent do you think you could get per month?
______________Rs

70. <u>(Ask everyone):</u> What is the total area of this house and land?

1. ____________________Kattha	2. ___________________Dhur

71. **<u>(Ask everyone):</u>** How old do you think is this house?

_____________________Years

72. <u>(Ask everyone):</u> In your opinion, what is the total value of this house and land in the current market?

1. ________Crores	2. ___________Lakh	3. _______thousand

******************************Thankyou******************************

<u>This part will be filled by Krishna:</u>

74. Was this house tested for coliform?

1. Yes
2. No

75. Presence of Coliform (Yes/No)?

1. Yes
2. No

76. Presence of fecal coliform? (Glows with UV light)?

1. Yes
2. No

STATA and R code

Chapter 1 Code:

```
*********************************************************************
*******************************
Figure 1.3

gen PayForDandaP = PayForDanda * 100
 gen WTP_P = WTP * 100
gen WTV_P = WTV * 100
gen Attend_Meetings_P = Attend_Meetings * 100
gen Join_WaterCG_P = Join_WaterCG * 100

**** WTP Graphs********
graph bar (mean) PayForDandaP, ///
blabel(total,format(%9.0f) size(small)) ///
over(LOCATION)  ///
ytitle ("Percent") ///
title("Percent of Population that believe the Government should fund
cleaning of the Danda", size(small)) ///
note("Source: Nepal Study Center, UNM, June 2016.")

*********************************************************************
*********************************


Figure 1.4
**** WTP Graphs
graph bar (mean) Importance_Danda, ///
blabel(total,format(%9.0f) size(small)) ///
ytitle ("Percent") ///
title("How Important is Danda River to you and your family?",
size(small)) ///
note("Source: Nepal Study Center, UNM, June 2016.")

*********************************************************************
**********************************

Figure 1.5
graph bar (mean) Financial_WTP, ///
blabel(total, format(%9.1f) size(small)) ///
ylabel(0 100 200 300 400 500) ///
yscale(range(0 500)) ///
over(LOCATION) ///
title("Average Annual Willingness to Pay to Clean Danda River") ///
subtitle("By Location") ///
ytitle("Payment (In Rupees)") ///
note("Source: Nepal Study Center, UNM, June 2016.")
```

```
******************************************************************************
**********************************

Figure 1.6
graph bar (mean) Time_WTP, ///
blabel(total, format(%9.1f) size(small)) ///
over(LOCATION) ///
ytitle("Hours") ///
title("Average Hours Willing to Volunteer Per Week to Clean
Danda") ///
subtitle("By Location") ///
note ("Source: Nepal Study Center, UNM, June 2016.")

******************************************************************************
**********************************

Figure 1.7

rename Q47 irr_choose

graph bar, over(irr_choose) ///
blabel(total, format(%9.1f) size(medium)) ///
bargap(-30) ///
ytitle("Percentage of farmers")  saving(irr_choose, replace) ///
title("Mode of irrigation used: Danda River?")
note("Source: Nepal Study Center, UNM. June, 2016")

******************************************************************************
**********************************

Figure 1.8
********source of water and what they do it with the
water*****************

rename Q24 DrinkinkWaterSource

gen DrinkingWaterPipedY = DrinkinkWaterSource ==1
gen DrinkingWaterPublicTapY = DrinkinkWaterSource ==2
gen DrinkingWaterTubewellY = DrinkinkWaterSource ==3
gen DrinkingWaterOtherY = DrinkinkWaterSource ==13


gen pipewater = DrinkingWaterPipedY * 100
gen publicwater = DrinkingWaterPublicTapY * 100
gen tubewellwater = DrinkingWaterTubewellY * 100
gen boringwater = DrinkingWaterOtherY * 100

graph bar (mean) pipewater publicwater tubewellwater boringwater, ///
over(LOCATION, label(labsize(vsmall))) blabel(total, format(%9.0f)
size(small)) ///
```

```
ytitle("Percentage", size(small))  saving(watersystem, replace)
yscale(range(0 70)) subtitle("(By Location)") ///
title("Types of Drinking Water Sources") legend(label(1 "Piped Water")
label(2 "Public Water") ///
label(3 "Tube Well Water") label(4 "Boring Water") size(vsmall)) ///
note("Source: Nepal Study Center, UNM. June, 2016")


**********************************************************************
**********************************

Figure 1.9

 gen pipe_treatment_pipe =.
replace pipe_treatment_pipe = 1 if (DrinkingWaterPipedY==1) &
(BoilOrFilterY==1)
 replace pipe_treatment_pipe = 0 if missing(pipe_treatment_pipe)


 gen public_treatment_tap =.
replace public_treatment_tap = 1 if (DrinkingWaterPublicTapY==1) &
(BoilOrFilterY==1)
 replace public_treatment_tap = 0 if missing(public_treatment_tap)


 gen treatment_tubewell =.
replace treatment_tubewell = 1 if (DrinkingWaterTubewellY==1) &
(BoilOrFilterY==1)
 replace treatment_tubewell = 0 if missing(treatment_tubewell)


 gen treatment_boring =.
replace treatment_boring = 1 if (DrinkingWaterTubewellY==1) &
(BoilOrFilterY==1)
 replace treatment_boring = 0 if missing(treatment_boring)

 gen pipe_treatment_pipeP = pipe_treatment_pipe * 100
gen public_treatment_tapP= public_treatment_tap * 100
gen treatment_tubewellP = treatment_tubewell * 100
gen treatment_boringP = treatment_boring * 100


graph bar (mean) pipe_treatment_pipeP public_treatment_tapP
treatment_tubewellP treatment_boringP, ///
b1title("Water Sources", size(small)) ///
ytitle("Percentage of households", size(small))  saving(watersystem1,
replace)  yscale(range(0 25))  ///
title("Water treatment behavaior by water source") legend(label(1
"Piped Water") label(2 "Public Water")label(3 "Tube Well
Water")label(4 "Boring Water") size(vsmall))
```

```
graph bar (mean) pipe_treatment_pipeP public_treatment_tapP
treatment_tubewellP treatment_boringP if LOCATION ==1, ///
b1title("Water Sources", size(small)) blabel(total, format(%9.0f)
size(vsmall)) ///
ytitle("Percentage", size(small))  saving(watersystem1, replace)
yscale(range(0 25))  ///
title("Siddharthanagar") legend(label(1 "Piped Water") label(2 "Public
Water")label(3 "Tube Well Water")label(4 "Boring Water") size(vsmall))


graph bar (mean) pipe_treatment_pipeP public_treatment_tapP
treatment_tubewellP treatment_boringP if LOCATION ==2, ///
b1title("Water Sources", size(small)) blabel(total, format(%9.0f)
size(vsmall)) ///
ytitle("Percentage", size(small))  saving(watersystem2, replace)
yscale(range(0 25))  ///
title("Basantpur") legend(label(1 "Piped Water") label(2 "Public
Water")label(3 "Tube Well Water")label(4 "Boring Water") size(vsmall))


graph bar (mean) pipe_treatment_pipeP public_treatment_tapP
treatment_tubewellP treatment_boringP if LOCATION ==3, ///
b1title("Water Sources", size(small)) blabel(total, format(%9.0f)
size(vsmall)) ///
ytitle("Percentage", size(small))  saving(watersystem3, replace)
yscale(range(0 25))  ///
title("Bagaha") legend(label(1 "Piped Water") label(2 "Public
Water")label(3 "Tube Well Water")label(4 "Boring Water") size(vsmall))


gr combine watersystem1.gph watersystem2.gph watersystem3.gph,
title("Water Treatment by Drinking Water Sources")   ///
subtitle("By Location") row(1) ///
note("Source: Nepal Study Center, UNM. June, 2016")

**********************************************************************
**********************************
```

Figure 1.10

```
/*Does your household own any of these following items?*/
//Durable Assets
gen radio = Q64_1==1 //Radio/Tape/CD player
gen bicycle = Q64_2==1 //Bicycle
gen motorcycle = Q64_3==1 //Motorcycle/Scooter
gen fan = Q64_4==1 //Fans
gen ac = Q64_5==1 //Air Conditioner
gen tv = Q64_6==1 //Television/deck
```

```
gen phone = Q64_7==1 //Telephone set/cordless phone/mobile phone/pager
gen sewing_machine = Q64_8==1 //Sewing machine
gen camera = Q64_9==1 //Camera (Still/Movie)

gen no_car = Q64_10==2 //Car
gen one_car = Q64_10==1 & Q64_10C==1 //One car
gen two_car = Q64_10==1 & Q64_10C==2 //Two Car
gen three_car = Q64_10==1 & Q64_10C==3 //Three Car

gen refrigerator = Q64_11==1 //Regrigerator or freezer
gen washing_machine = Q64_12==1 //Washing machine
gen computer = Q64_13==1 //Computer

//Housing Characteristics
gen garage = Q64_14==1 //Motor Garage
gen inverter = Q64_15==1 //Inverter or solar for electricity
gen garden = Q64_16==1 //Garden
gen window = Q64_17==1 //Window in every room of the house?
gen alt_water = Q64_18==1 //Alternative source of water inside the
compound?
gen attach_bathroom = Q64_19==1 //Attach bathroom

gen one_bedroom = Q64_20<2 //1 bedroom
gen two_to_five_bedroom = Q64_20>=2 & Q64_20<6 //2-5 bedroom
gen morethan_five_bedroom = Q64_20>5 //>5 bedroom

gen own_house = Q66==2 //Rental place or private property

//family: Do I need to add the number of people in a household?




#delimit;
global assets "radio bicycle motorcycle fan ac tv phone sewing_machine
camera one_car two_car three_car refrigerator
washing_machine computer garage inverter garden window alt_water
attach_bathroom own_house one_bedroom two_to_five_bedroom
morethan_five_bedroom";

#delimit cr
factor $assets, pcf
predict asset_index
xtile quintile=asset_index, nq(5)
tab quintile

**********************************************************************
**********************************
```

Chapter 2 Code

```
**************************************************************************************************
Table 2.3 & Table 2.4

library(mlogit)
library(gmnl)
library("readstata13")
library(memisc)
library(dplyr)


x<-read.dta13("/Users/samratkunwar/Google Drive/Dissertation Chapters/
survey data/CE long format data/CE_long_data.dta")
x<-x[,c(1:9,58,254:264)]
head(x)
x<-x[,c(1:12,20,14:16,21,17:19,13)]
x$certainty_question<-as.numeric(x$certainty_question)

#-----------------------------------------------------------------------
----------#

x$asc<-as.numeric(x$alt==1|x$alt==2)

x$bank100<-as.numeric(x$bank==100)
x$bank150<-as.numeric(x$bank==150)

x$trees40<-as.numeric(x$trees==40)
x$trees80<-as.numeric(x$trees==80)

x$com<-as.numeric(x$regulation=="com")
x$mun<-as.numeric(x$regulation=="mun")
x$gov<-as.numeric(x$regulation=="gov")

danda<-mlogit.data(x,choice="choice_final",shape="long",alt.var =
"alt",chid.var = "caseid", id="HOUSEID")

#-----------------------------------------------------------------------
---#
#basic multinomial logit
f.clogit<-
mlogit(choice_final~asc+quality+bank100+bank150+trees40+trees80+monito
ring+mun+gov+cost|0, danda, reflevel = 3)
summary(f.clogit)

#IIA test clogit

f.clogit.noalt1<-
```

```
mlogit(choice_final~asc+quality+bank100+bank150+trees40+trees80+monito
ring+mun+gov+cost|0, danda,
                        reflevel = 3, alt.subset = c(2,3))
summary(f.clogit.noalt1)

f.clogit.noalt2<-
mlogit(choice_final~asc+quality+bank100+bank150+trees40+trees80+monito
ring+mun+gov+cost|0, danda,
                        reflevel = 3, alt.subset = c(1,3))
summary(f.clogit.noalt2)

hmftest(f.clogit,f.clogit.noalt1)
hmftest(f.clogit,f.clogit.noalt2)
#---------------------------------------------------------------------
---#
#mixed logit
f.gmnl.mixl<-
gmnl(choice_final~quality+bank100+bank150+trees40+trees80+monitoring+m
un+gov+cost+asc|0,
                  data= danda,
                  model="mixl",
                  R=1000,
                  panel = T,
                  notscale = c(rep(0,11),1),
                  ranp = c(asc="n",qualityall="n",qualityboa="n",

qualitybaf="n",bank100="n",bank150="n",trees40="n",trees80="n"
                           ,monitoring="n",mun="n",gov="n"))



summary(f.gmnl.mixl)
AIC(f.gmnl.mixl)
BIC(f.gmnl.mixl)

#---------------------------------------------------------------------
---#
#gmnl-2 simple model

f.gmnl.unc<-
gmnl(choice_final~cost+quality+bank100+bank150+trees40+trees80+monitor
ing+mun+gov+asc|0,
                 data= danda,
                 model="gmnl",
                 R=920,
                 panel = T,
                 notscale = c(rep(0,11),1),
                 ranp = c(asc="n",qualityall="n",qualityboa="n",

qualitybaf="n",bank100="n",bank150="n",trees40="n",trees80="n"
```

```
                            ,monitoring="n",mun="n",gov="n"),print.init
= T)


summary(f.gmnl.unc)
wtp.gmnl(f.gmnl.unc, wrt = "cost")
AIC(f.gmnl.unc)
BIC(f.gmnl.unc)
#----------------------------------------------------------------------
---#
#gmnl model with uncertainty

danda$uncertain<-as.numeric(danda$certainty_value==1|
danda$certainty_value==2)
danda$certain<-as.numeric(danda$certainty_value==4|
danda$certainty_value==5)

f.gmnl.unc2<-
gmnl(choice_final~cost+quality+bank100+bank150+trees40+trees80+monitor
ing+mun+gov+asc|0|0|0|certain+uncertain-1,
                  data= danda,
                  model="gmnl",
                  R=1000,
                  panel = T,
                  notscale = c(rep(0,11),1),
                  ranp = c(asc="n",qualityall="n",qualityboa="n",

qualitybaf="n",bank100="n",bank150="n",trees40="n",trees80="n"
                            ,monitoring="n",mun="n",gov="n"),nobs=lengt
h(danda$choice)
                  ,print.init = T,haltons = NA,
                  start =
c(-0.001049511,1.894698072,0.152737242,0.906729335,0.25,0.30,0.9630052
10,1.444323578,

0.353097618,-0.534636617,-0.906178109,0.550795083,0.000000000,0.000000
000,0.100000000,0.100000000,

0.100000000,0.100000000,0.100000000,0.100000000,0.100000000,0.10000000
0,0.100000000,0.100000000,
                             0.100000000,0.100000000,0.100000000))

summary(f.gmnl.unc2)
AIC(f.gmnl.unc2)
BIC(f.gmnl.unc2)

wtp.gmnl(f.gmnl.unc2, wrt = "cost")
#----------------------------------------------------------------------
#
```

```
#computing implicit wtp from the above model
wtp.ind.unc<-effect.gmnl(f.gmnl.unc2,par =
c("qualityall","qualityboa","qualitybaf",

"bank100","bank150","trees40","trees80","monitoring","mun","gov"),
                         effect = "wtp",wrt = "cost")


#export to excel
wtp.ind.df<-as.data.frame(wtp.ind.unc)
wtp.ind.df<-data.frame(mapply(`*`,wtp.ind.df,-1))
wtp.ind.df<-wtp.ind.df[,c(1:10)]

y<-x %>%
  group_by(HOUSEID) %>%
  summarise_each(funs(paste(., collapse = " ")))
y<-as.data.frame(y[,c(1,11,12)])
wtp.ind.df<-cbind(y,wtp.ind.df)

write.csv(wtp.ind.df,"/Users/samratkunwar/Google Drive/Dissertation
Chapters/Chapter 1 - CE/CE Analysis - danda/GMNL/Final Code /
Individual WTP/individual wtp sep 17 - uncertainty.csv")
#-------------------------------------------------------------------
#
#extracting the output
stargazer(f.clogit,no.space = T,type="html",out = "/Users/
samratkunwar/Google Drive/Dissertation Chapters/Chapter 1 - CE/CE
Analysis - danda/GMNL/GMNL data/ClogitOutput.html")
GmnlOutput<-mtable(f.gmnl.mixl,f.gmnl.unc,f.gmnl.unc2,
                   signif.symbols = c("*" = .099,
                                      "**" = .05,
                                      "***"=.01))
GmnlOutput
write.mtable(GmnlOutput,format = "HTML",file = "/Users/samratkunwar/
Google Drive/Dissertation Chapters/Chapter 1 - CE/CE Analysis - danda/
GMNL/GMNL data/GmnlOutput.html")
#-------------------------------------------------------------------
#
#comuting WTP from the best model

wtp.mixl<-wtp.gmnl(f.gmnl.mixl, wrt = "cost")
wtp.gmnl<-wtp.gmnl(f.gmnl.unc, wrt = "cost")
wtp.gmnl2<-wtp.gmnl(f.gmnl.unc2, wrt = "cost")

#-------------------------------------------------------------------
---------------#
Table 2.5

#Plotting WTP Confidence Intervals
```

```
#computing implicit wtp from the above model
wtp.ind.unc<-effect.gmnl(f.gmnl.unc2,par =
c("qualityall","qualityboa","qualitybaf",

"bank100","bank150","trees40","trees80","monitoring","mun","gov"),
                         effect = "wtp",wrt = "cost")


#export to excel
wtp.ind.df<-as.data.frame(wtp.ind.unc)
wtp.ind.df<-data.frame(mapply(`*`,wtp.ind.df,-1))
wtp.ind.df<-wtp.ind.df[,c(1:10)]

y<-x %>%
  group_by(HOUSEID) %>%
  summarise_each(funs(paste(., collapse = " ")))
y<-as.data.frame(y[,c(1,11,12)])
wtp.ind.df<-cbind(y,wtp.ind.df)

write.csv(wtp.ind.df,"/Users/samratkunwar/Google Drive/Dissertation
Chapters/Chapter 1 - CE/CE Analysis - danda/GMNL/Final Code /
Individual WTP/individual wtp sep 17 - uncertainty.csv")
#---------------------------------------------------------------------
#
#extracting the output
stargazer(f.clogit,no.space = T,type="html",out = "/Users/
samratkunwar/Google Drive/Dissertation Chapters/Chapter 1 - CE/CE
Analysis - danda/GMNL/GMNL data/ClogitOutput.html")
GmnlOutput<-mtable(f.gmnl.mixl,f.gmnl.unc,f.gmnl.unc2,
                   signif.symbols = c("*" = .099,
                                      "**" = .05,
                                      "***"=.01))
GmnlOutput
write.mtable(GmnlOutput,format = "HTML",file = "/Users/samratkunwar/
Google Drive/Dissertation Chapters/Chapter 1 - CE/CE Analysis - danda/
GMNL/GMNL data/GmnlOutput.html")
#---------------------------------------------------------------------
#
#comuting WTP from the best model

wtp.mixl<-wtp.gmnl(f.gmnl.mixl, wrt = "cost")
wtp.gmnl<-wtp.gmnl(f.gmnl.unc, wrt = "cost")
wtp.gmnl2<-wtp.gmnl(f.gmnl.unc2, wrt = "cost")

#---------------------------------------------------------------------
---------------#
Table 2.5

#Plotting WTP Confidence Intervals
```

```
#Step 1:
# #extracting CI from mixl
# ci.mixl<-as.data.frame(getSummary.gmnl(f.gmnl.mixl,
0.05)$coef[,c(1,5,6)])
# ci.mixl$mean<-ci.mixl$est/ci.mixl[1,1]
# ci.mixl$lwr_value<-ci.mixl$lwr/ci.mixl[1,1]
# ci.mixl$upr_value<-ci.mixl$upr/ci.mixl[1,1]
# ci.mixl<-ci.mixl[c(2:9),c(4:6)]
# ci.mixl<-ci.mixl*(-1)

#extracting CI from GMNL - no uncertainty
ci.gmnl<-as.data.frame(getSummary.gmnl(f.gmnl.unc,
0.05)$coef[,c(1,5,6)])
ci.gmnl$mean<-ci.gmnl$est/ci.gmnl[1,1]
ci.gmnl$lwr_value<-ci.gmnl$lwr/ci.gmnl[1,1]
ci.gmnl$upr_value<-ci.gmnl$upr/ci.gmnl[1,1]
ci.gmnl<-ci.gmnl[c(2,4,6:11),c(4:6)] #removing the qualityboa and
bank100 non significant variable
ci.gmnl<-ci.gmnl[rev(rownames(ci.gmnl)),]
ci.gmnl<-ci.gmnl*-1
ci.gmnl<-ci.gmnl[c(1,2,3,4,5,7,6,8,9),]
#ci.gmnl<-ci.gmnl[c(2,3,4,5,6,7,10,11),]


#extracting CI from GMNL - uncertainty
ci.gmnl.unc<-
as.data.frame(getSummary.gmnl(f.gmnl.unc2,0.05)$coef[,c(1,5,6)])
ci.gmnl.unc$mean<-ci.gmnl.unc$est/ci.gmnl.unc[1,1]
ci.gmnl.unc$lwr_value<-ci.gmnl.unc$lwr/ci.gmnl.unc[1,1]
ci.gmnl.unc$upr_value<-ci.gmnl.unc$upr/ci.gmnl.unc[1,1]
ci.gmnl.unc<-ci.gmnl.unc[c(2,4,6:11),c(4:6)] #removing the qualityboa
and bank100 non significant variable
ci.gmnl.unc<-ci.gmnl.unc[rev(rownames(ci.gmnl.unc)),]
ci.gmnl.unc<-ci.gmnl.unc*-1
#ci.gmnl.unc<-ci.gmnl.unc[c(1,2,3,4,5,7,6,8),]
#ci.gmnl.unc<-ci.gmnl.unc[c(2,3,4,5,6,7,10,11),]


#Plotting WTP Confidence Intervals

WTP_labels<- c("Regulation:Government", "Regulation:Municipality",
"Monitoring & Educational Progarm",
               "Tree Plantation: 80%","Tree Plantation:
40%","Riverbank protection: 300 feet","Quality: Boat and Fish",
"Quality:All")

plot_data<- data.frame(
  xmin = c(1, 1.5, 3, 3.5, 5, 5.5, 7, 7.5, 9, 9.5, 11, 11.5, 13, 13.5,
15, 15.5)
```

```
  , ymin = c(ci.gmnl$lwr_value, ci.gmnl.unc$lwr_value)
  , ymax = c(ci.gmnl$upr_value,ci.gmnl.unc$upr_value)
  , ymean = c(ci.gmnl$mean,ci.gmnl.unc$mean)
  , Model = rep(c("GMNL- Excluding Preference Uncertainty","GMNL-
Including Preference Uncertainty"), each=8)
  , id = factor(WTP_labels, levels = WTP_labels)
)



plot_data$"xmax"; plot_data$"xmin" + 1

library(ggplot2)
library(ggthemes)



WTP_plot_pointrange<- ggplot(plot_data, aes(x = id, y = ymean,
                                            color=Model, size=25)) +
  theme(axis.text.x = element_text(angle=70,
vjust=0.5,color="black",size=12),axis.text.y =
element_text(color="black",size = 10),
        panel.background = element_blank(),
        axis.line = element_line(colour="black"))+
  #theme_classic() +
  #geom_hline(yintercept = 0, color = grey(0.1)) +
  geom_pointrange(aes(ymin=ymin, ymax=ymax)
                  , size = .5
                  , position = position_dodge(width = 0.6))+
  labs(x = "Attributes"
       , y = "Confidence interval of marginal WTP estimators (Rs./
Year)") +
  scale_color_manual(values = c("#999999", "#E69F00")) +
  coord_flip()

WTP_plot_pointrange



#zooming in the bank and tree wtp
#WTP_plot_pointrange + coord_flip(xlim = c(4,5),ylim = c(0,40))


######################################################################
############
#K-R Confidence Interval
coef <- f.gmnl.mixl$coef
src <- c(9,1) #index row and column to extract
sbeta <- coef[src] #extract just regression coeffs
cov_coef <- vcov(f.gmnl.mixl)[1:9,1:9]
```

```
scov_b <- cov_coef[src,src] #cov_coef
#normally draw betas
sbeta_sim <- rmultinorm(100000, mu=sbeta, vmat=scov_b, tol = 1e-10)
#defines sbeta_sim
swtp <- function(sbeta_sim){
  b2 <- sbeta_sim[,1]
  b8 <- sbeta_sim[,2]
  fb =-(b2)/b8
  return( fb )
}
swtp <- eval(swtp(sbeta_sim)) #swtpvalues
#mean(swtp) #'mean of simulated WTP'
quantiles <- quantile(swtp, c(.025, .975)) #'Quantiles calulation of
simulated series'
#quantiles #"Confidence Interval of WTP_simulated"
#summary(quantiles) #'summary quantiles info'
#"Mean and Confidence Interval of WTP_normal"
m<-round(mean(swtp), 2)
l<-round(min(quantiles), 2)
h<-round(max(quantiles), 2)
c<-c(l,m,h)
c

save.image(file = "/Users/samratkunwar/Google Drive/Dissertation
Chapters/Chapter 1 - CE/CE Analysis - danda/GMNL/Final Code /
GMNL_final_output.RData")

**********************************************************************
**************************
```

Chapter 3 Code

```
***********************************************************************
************************

clear all
set more off
set graphics off
use "/Users/sbkunwar/Google Drive/Dissertation Chapters/chapter 2 -
knowledge gap/STATA and R codes/clean water dataset/
CleanWaterDataset_Dec24.dta"
cd "/Users/sbkunwar/Google Drive/Dissertation Chapters/chapter 2 -
knowledge gap/Journal Submission/WEP R&R/STATA Folder/Graph and Table"

***********************************************************************
*********
//Tabular:

tab risk_perception
tab risk_rank
tab gap

tab treat_water risk_rank, row nofreq
tab treat_water ecoli_present, row nofreq


//tabulate two-way with pearson chi2

tab treat_water gap, row nofreq chi2 exact
tab risk_perception ecoli_presentY, row nofreq chi2

***********************************************************************
*********

//Basic Probit Model

//What is the relationship between information gap and treatment
behavior?
probit treat_water ib2.gap [pw=hh_weight_method2], vce(cluster
uniquewards)

//What is the impact of perception and ecoli on treatment behavior?
probit treat_water ecoli_presentY risk_rank [pw=hh_weight_method2],
vce(cluster uniquewards)

//What is the impact of joint interaction on treatment behavior?
probit treat_water ecoli_presentY##risk_rank [pw=hh_weight_method2],
vce(cluster uniquewards)
pwcompare ecoli_presentY##risk_rank, effect post

***********************************************************************
```

```
*********
//Extended Probit Model with Interaction

//Model 1 with basic control variable (only water characteristics)
probit treat_water ecoli_presentY##risk_rank ib2.water_source
water_taste_satisfaction ///
[pw=hh_weight_method2], vce(cluster uniquewards) nolog
margins ecoli_presentY##risk_rank, pwcompare
mat tab_1 = r(table_vs)'
mat list tab_1

pwcompare ecoli_presentY##risk_rank, effect post




//Model 2 with moderate control variable (water and knowledge
characteristics)
probit treat_water ecoli_presentY##risk_rank ib2.water_source
water_taste_satisfaction SomeCollege scientific_knowledge  SickY ///
[pw=hh_weight_method2], vce(cluster uniquewards) nolog
margins ecoli_presentY##risk_rank, pwcompare
mat tab_2 = r(table_vs)'
mat list tab_2

pwcompare ecoli_presentY##risk_rank, effect post



//Model 3 with full control variable
probit treat_water ecoli_presentY##risk_rank ib2.water_source
water_taste_satisfaction SomeCollege scientific_knowledge  SickY
i.wealth BrahminChett children rental urban ///
[pw=hh_weight_method2], vce(cluster uniquewards) nolog
margins, dydx(_all)
margins ecoli_presentY##risk_rank, pwcompare
mat tab_3 = r(table_vs)'
mat list tab_3

pwcompare ecoli_presentY##risk_rank, effect post

**********************************************************************
*********
//Extended Probit Model with Interaction for different treatment
models

//--------------------------------------------------------------------
--

//Model with full control variable for Boil
```

```
probit Boil ecoli_presentY##risk_rank ib2.water_source
water_taste_satisfaction SomeCollege scientific_knowledge  SickY
i.wealth BrahminChett children rental urban ///
[pw=hh_weight_method2], vce(cluster uniquewards) nolog
margins ecoli_presentY##risk_rank, pwcompare
mat tab_boil = r(table_vs)'
mat list tab_boil

pwcompare ecoli_presentY##risk_rank, effect post


//----------------------------------------------------------------------
--

//Model with full control variable for Filter
probit Filter ecoli_presentY##risk_rank ib2.water_source
water_taste_satisfaction SomeCollege scientific_knowledge  SickY
i.wealth BrahminChett children rental urban ///
[pw=hh_weight_method2], vce(cluster uniquewards) nolog
margins ecoli_presentY##risk_rank, pwcompare
mat tab_filter = r(table_vs)'
mat list tab_filter

pwcompare ecoli_presentY##risk_rank, effect post
*/
**********************************************************************
*********

// Biprobit full model

gen wide_gap = gap==1|gap==4
gen min_gap = gap==2|gap==3
biprobit (treat_water = min_gap water_taste_satisfaction SomeCollege
scientific_knowledge  SickY i.wealth BrahminChett children rental
urban) ///
(group3 = community_perception wash_utensil ib2.water_source
water_taste_satisfaction SomeCollege SickY scientific_knowledge
i.wealth BrahminChett children rental  urban)[pw=hh_weight_method2],
vce(cluster uniquewards) nolog
**********************************************************************
*********
```

Chapter 4 Code

```
********************************************************************
*************************
Example of Rainfall and Temperature data for one station

***Winter Temperature/Precipitation
clear all
if "`c(version)'"=="13.1"{
cd "E:\sus dev\STATA\dataset"
local inpath "E:\sus dev\climate\csv files"
 }
 else{
 cd "F:\Class Research Papers\Sustainable Development I\STATA\dataset"
local inpath "F:\Class Research Papers\Sustainable Development
I\climate stata code\csv files"
 }

insheet using "`inpath'/0104_rain.csv",clear

generate date=td(01jan1971)+ _n-1
format date %td

//Precipitation
gen precipitation = real(v2)
drop v1 v2

gen dmo=mofd(date)
label var dmo "date year/month"

format dmo %tm
gen month=month(date)
gen year=year(date)
gen a = dmo

egen prec_win=mean(precipitation), by(dmo)
drop if month<12 & month>2

collapse (first)prec_win, by(a dmo)

egen mean_prec_win = mean(prec_win)
egen prec_win_fivyr = mean(prec_win) if a>491 //avg from 2000-endyr
egen sd_prec = sd(prec_win)

collapse (firstnm)mean_prec_win prec_win_fivyr sd_prec
gen z_prec_win = (prec_win_fivyr-mean_prec_win)/(sd_prec)
gen z_prec2_win = z_prec_win*z_prec_win
keep z_prec_win z_prec2_win

gen belt=2
gen district = 73
```

```
label var z_prec_win "mean (standarized) total winter rainfall
1971-2008"
label var z_prec2_win "square of winter mean precipitation"

save rain_win_0104.dta, replace



// temperature
insheet using "`inpath'/0104_temp.csv",clear

generate date=td(01jan1978)+ _n-1
format date %td
gen tmax = real(v2)
gen tmin = real(v3)

drop v1 v2 v3

gen dmo=mofd(date)
format dmo %tm
gen a = dmo

gen month=month(date)
gen year=year(date)

egen temp_win=mean(tmax + tmin), by(dmo)
drop if month<12 & month>2

collapse (first) temp_win, by(a dmo)

egen mean_temp_win = mean(temp_win)
egen temp_win_fivyr = mean(temp_win) if a>491 //avg from 2000-endyr
egen sd_temp = sd(temp_win)

collapse (firstnm)mean_temp_win temp_win_fivyr sd_temp
gen z_temp_win = (temp_win_fivyr-mean_temp_win)/(sd_temp)
gen z_temp2_win = z_temp_win*z_temp_win
keep z_temp_win z_temp2_win

gen belt=2
gen district = 73

label var z_temp_win "mean (standarized) total winter temperature
1978-2008"
label var z_temp2_win "square of mean temperature"

merge 1:1 (district) using rain_win_0104.dta
keep if _merge==3
drop _merge
```

```
save 0104_win.dta, replace


// Summer Temperature/Precipitation
//Precipitation
insheet using "`inpath'/0104_rain.csv",clear
generate date=td(01jan1971)+ _n-1
format date %td

gen precipitation = real(v2)

drop v1 v2


gen dmo=mofd(date)
label var dmo "date year/month"

format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen prec_sum=mean(precipitation), by(dmo)
keep if month==6 | month==7 | month==8

collapse (first)prec_sum, by(a dmo)

egen mean_prec_sum = mean(prec_sum)
egen prec_sum_fivyr = mean(prec_sum) if a>485 //avg from 2000-endyr
egen sd_prec = sd(prec_sum)

collapse (firstnm)mean_prec_sum prec_sum_fivyr sd_prec
gen z_prec_sum = (prec_sum_fivyr-mean_prec_sum)/(sd_prec)
gen z_prec2_sum = z_prec_sum*z_prec_sum
keep z_prec_sum z_prec2_sum

gen belt=2
gen district = 73

label var z_prec_sum "mean total (standarized) summer rainfall
1971-2008"
label var z_prec2_sum "square of mean precipitation"


merge m:m (district) using 0104_win.dta
keep if _merge==3
drop _merge
```

```
save rain_sum_0104.dta, replace


// temperature
insheet using "`inpath'/0104_temp.csv",clear

generate date=td(01jan1978)+ _n-1
format date %td
gen tmax = real(v2)
gen tmin = real(v3)

drop v1 v2 v3

gen dmo=mofd(date)
format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen temp_sum=mean(tmax + tmin), by(dmo)
keep if month==6 | month==7 | month==8

collapse (first) temp_sum, by(a dmo)

egen mean_temp_sum = mean(temp_sum)
egen temp_sum_fivyr = mean(temp_sum) if a>485 //avg from 2000-endyr
egen sd_temp = sd(temp_sum)

collapse (firstnm)mean_temp_sum temp_sum_fivyr sd_temp
gen z_temp_sum = (temp_sum_fivyr-mean_temp_sum)/(sd_temp)
gen z_temp2_sum = z_temp_sum*z_temp_sum
keep z_temp_sum z_temp2_sum


gen belt=2
gen district = 73

label var z_temp_sum "mean total (standarized) summer temperature
1978-2008"
label var z_temp2_sum "square of mean temperature"


merge 1:1 (district) using rain_sum_0104.dta
keep if _merge==3
drop _merge

save 0104_sum.dta, replace

//Spring Temperature/Precipitation
//Precipitation
```

```
insheet using "`inpath'/0104_rain.csv",clear
generate date=td(01jan1971)+ _n-1
format date %td

gen precipitation = real(v2)

drop v1 v2


gen dmo=mofd(date)
label var dmo "date year/month"

format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen prec_spr=mean(precipitation), by(dmo)
keep if month==3 | month==4 | month==5

collapse (first)prec_spr, by(a dmo)

egen mean_prec_spr = mean(prec_spr)
egen prec_spr_fivyr = mean(prec_spr) if a>472 //avg from 2000-endyr
egen sd_prec = sd(prec_spr)

collapse (firstnm)mean_prec_spr prec_spr_fivyr sd_prec
gen z_prec_spr = (prec_spr_fivyr-mean_prec_spr)/(sd_prec)
gen z_prec2_spr = z_prec_spr*z_prec_spr
keep z_prec_spr z_prec2_spr

gen belt=2
gen district = 73

label var z_prec_spr "mean total (standarized) spring rainfall
1971-2008"
label var z_prec2_spr "square of mean precipitation"

merge 1:1 (district) using 0104_sum.dta
keep if _merge==3
drop _merge

save rain_spr_0104.dta, replace

// temperature
insheet using "`inpath'/0104_temp.csv",clear

generate date=td(01jan1978)+ _n-1
format date %td
gen tmax = real(v2)
```

```
gen tmin = real(v3)

drop v1 v2 v3

gen dmo=mofd(date)
format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen temp_spr=mean(tmax + tmin), by(dmo)
keep if month==3 | month==4 | month==5

collapse (first) temp_spr, by(a dmo)

egen mean_temp_spr = mean(temp_spr)
egen temp_spr_fivyr = mean(temp_spr) if a>485 //avg from 2000-endyr
egen sd_temp = sd(temp_spr)

collapse (firstnm)mean_temp_spr temp_spr_fivyr sd_temp
gen z_temp_spr = (temp_spr_fivyr-mean_temp_spr)/(sd_temp)
gen z_temp2_spr = z_temp_spr*z_temp_spr
keep z_temp_spr z_temp2_spr

gen belt=2
gen district = 73

label var z_temp_spr "mean (standarized) total spring temperature
1978-2008"
label var z_temp2_spr "square of mean temperature"

merge 1:1 (district) using rain_spr_0104.dta
keep if _merge==3
drop _merge

save 0104_spr.dta, replace

//Fall Temperature/Precipitation
//Precipitation
insheet using "`inpath'/0104_rain.csv",clear
generate date=td(01jan1971)+ _n-1
format date %td

gen precipitation = real(v2)

drop v1 v2


gen dmo=mofd(date)
label var dmo "date year/month"
```

```
format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen prec_fal=mean(precipitation), by(dmo)
keep if month==9 | month==10 | month==11

collapse (first)prec_fal, by(a dmo)
egen mean_prec_fal = mean(prec_fal)
egen prec_fal_fivyr = mean(prec_fal) if a>478 //avg from 2000-endyr
egen sd_prec = sd(prec_fal)

collapse (firstnm)mean_prec_fal prec_fal_fivyr sd_prec
gen z_prec_fal = (prec_fal_fivyr-mean_prec_fal)/(sd_prec)
gen z_prec2_fal = z_prec_fal*z_prec_fal
keep z_prec_fal z_prec2_fal

gen belt=2
gen district = 73

label var z_prec_fal "mean (standarized) total fall rainfall
1971-2008"
label var z_prec2_fal "square of  mean precipitation"

merge 1:1 (district) using 0104_spr.dta
keep if _merge==3
drop _merge

save rain_fal_0104.dta, replace

// temperature
insheet using "`inpath'/0104_temp.csv",clear

generate date=td(01jan1978)+ _n-1
format date %td
gen tmax = real(v2)
gen tmin = real(v3)

drop v1 v2 v3

gen dmo=mofd(date)
format dmo %tm
gen a = dmo
gen month=month(date)
gen year=year(date)

egen temp_fal=mean(tmax + tmin), by(dmo)
keep if month==9 | month==10 | month==11
```

```
collapse (first) temp_fal, by(a dmo)
egen mean_temp_fal = mean(temp_fal)
egen temp_fal_fivyr = mean(temp_fal) if a>485 //avg from 2000-endyr
egen sd_temp = sd(temp_fal)

collapse (firstnm)mean_temp_fal temp_fal_fivyr sd_temp
gen z_temp_fal = (temp_fal_fivyr-mean_temp_fal)/(sd_temp)
gen z_temp2_fal = z_temp_fal*z_temp_fal
keep z_temp_fal z_temp2_fal

gen belt=2
gen district = 73

label var z_temp_fal "mean (standarized) total fall temperature
1978-2006"
label var z_temp2_fal "square of mean temperature"

merge 1:1 (district) using rain_fal_0104.dta
keep if _merge==3
drop _merge

save 0104.dta, replace

**********************************************************************
***************************

Regression:

clear all
cd "f:\sus dev\STATA\dataset"

//probit
use nllsfinal.dta
gen lrev = ln(net_revenue)
gen ldist = ln(distinputmkt+1)
gen lelevation = ln(elevation)
gen ltinc = ln(tot_income+1)
gen lvlue = ln(landvalue) if landvalue>0
gen dsoil = domsoil==3 //dsoil=1 is good soil
gen education = edu<17 //literate people
gen credit = credit_amt/1000 //(thousandth)
/*
describe irr_choose mean_temp_fal mean_temp_spr mean_temp_win
mean_temp_sum mean_prec_fal mean_prec_spr mean_prec_win mean_prec_sum
net_revenue ///
prec2_fal prec2_sum prec2_win prec2_spr temp2_fal temp2_sum temp2_win
temp2_spr logdischarge credit_amt hh_farmsize distinputmkt age sex
log_hsize ///
*/
```

```
sum irr_choose z_prec_win z_prec2_win z_temp_win z_temp2_win
z_prec_sum z_prec2_sum z_temp_sum z_temp2_sum ///
z_prec_spr z_prec2_spr z_temp_spr z_temp2_spr z_prec_fal z_prec2_fal
z_temp_fal z_temp2_fal credit_amt ///
hh_farmsize distinputmkt age gender log_hsize

// OLS estimation
probit irr_choose z_prec_win  z_temp_win  z_prec_sum  z_temp_sum  ///
z_prec_spr  z_temp_spr  z_prec_fal  z_temp_fal i.domsoil, robust

predict irr_choosehat, xb
gen pdf_gammaz = 1/(sqrt(2*(_pi)))*exp(-0.5*(irr_choosehat^2))
gen cdf_gammaz = normprob(irr_choosehat)
gen imr = pdf_gammaz / cdf_gammaz

reg lvlue z_prec_win z_prec2_win z_temp_win z_temp2_win z_prec_sum
z_prec2_sum z_temp_sum z_temp2_sum ///
z_prec_spr z_prec2_spr z_temp_spr z_temp2_spr z_prec_fal z_prec2_fal
z_temp_fal z_temp2_fal credit ///
hh_farmsize /*ldist*/ electricity age gender /*hhsize*/ education
log_hsize distinputmkt elevation i.domsoil imr if irr_choose == 1,
robust beta

margins, eydx(z_prec_win z_prec_sum z_prec_spr z_prec_fal ) atmean

margins, eydx(z_temp_win z_temp_sum z_temp_spr z_temp_fal ) atmean
*********************************************************************
***************************
```

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1. Reference cited in Chapter 1
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