Adoption Determinants and Economic Benefits of Integrated Pest Management for Nepali Vegetable Farmers

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ABSTRACT

The majority of Nepal's population relies on agriculture, so invasive and native pests' ability to reduce farmers' crop yields is a significant concern. To protect farm households' food security and livelihoods, it is imperative to find effective pest management products and practices. Integrated pest management (IPM) is an arguably cheaper and less harmful alternative to conventional synthetic pesticides and is a way of managing and preventing agricultural pests using different levels of control methods (e.g., biological, cultural, and chemical) that have minimal adverse environmental and human health impacts. This study provides information on the extent of IPM practices by Nepali vegetable farmers, adds to the understanding of factors that influence the IPM adoption decision, and compares the economic benefits and performance of IPM to other conventional pest management practices. Our survey of 346 vegetable farmers in four districts throughout Nepal provides the primary data we use in our analysis. We distinguish practices into two categories: simple IPM practices that are commonly used and require limited knowledge and complex practices that typically require more knowledge and conscious use of IPM itself. We use a probit model to determine the factors that significantly affect the decision to adopt complex IPM practices. Our results find two explanatory variables that consistently affect complex IPM adoption: gender and IPM training. We compare the costs and benefits of using IPM to other conventional pest management practices by analyzing results from experimental field trials conducted in Nepal's Banke and Surkhet districts. Using an economic surplus approach, we estimate the market-level benefits of using IPM practices for three vegetables in Banke and four vegetables in Surkhet. The results predict cumulative IPM benefits of $1.06 to $1.44 million across the two districts.

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GENERAL AUDIENCE ABSTRACT

The majority of Nepal's population relies on agriculture, so invasive and native pests' ability to reduce farmers' crop yields is a significant concern. To protect farm households' food security and livelihoods, it is imperative to find effective pest management products and practices. Integrated pest management (IPM) is an arguably cheaper and less harmful alternative to conventional synthetic pesticides and is a way of managing and preventing agricultural pests using different levels of control methods (e.g., crop rotation, weeding, pheromones to disrupt mating) that have minimal adverse environmental and human health impacts. This study provides information on the extent of IPM practices by Nepali vegetable farmers, adds to the understanding of factors that influence the IPM adoption decision, and compares the economic benefits and performance of IPM to conventional synthetic pesticides. Our survey of 346 vegetable farmers in four districts throughout Nepal provides the primary data we use in our analysis. We distinguish practices into two categories: simple IPM practices that are commonly used and require limited knowledge and complex practices that typically require more knowledge and conscious use of IPM itself. Various statistical methods are used and find that gender and IPM training consistently affect the decision to adopt complex IPM practices. Compared to female Nepali vegetable farmers, males are more likely to adopt complex practices. In addition, attending an IPM training event increases the likelihood of farmers using complex IPM practices. We use data from field trials of farmers in Surkhet and Banke, IPM adoption rates from the survey, and information on Nepal's vegetable market to calculate the economic benefits of farmers using complex IPM practices for tomato, cauliflower, onion, and cucumber production. The results predict cumulative IPM benefits of \$1.06 to \$1.44 million to vegetable consumers and producers across the two districts.

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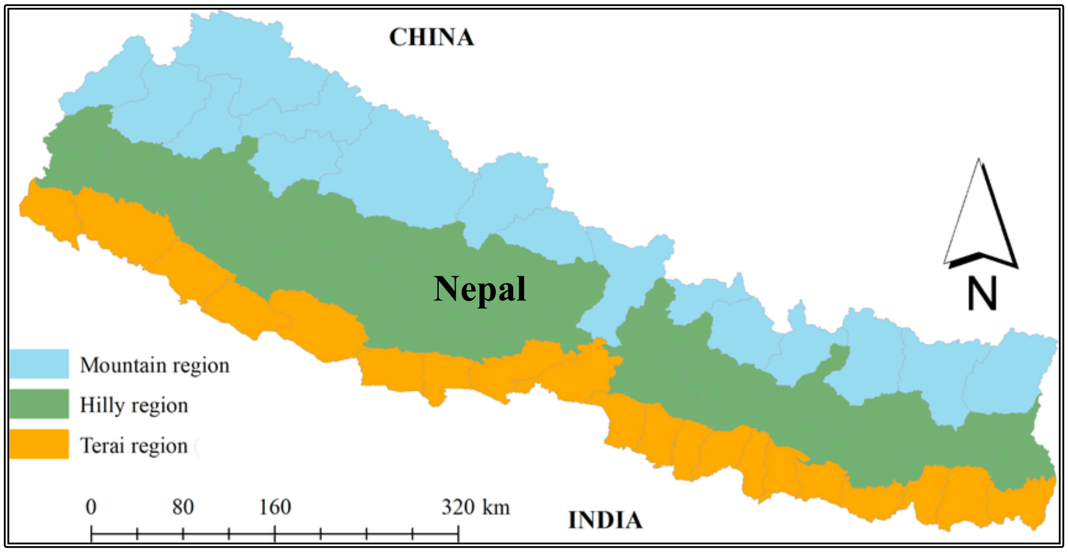
Chapter 1. Introduction

1.1 Problem Statement

As the world's population keeps growing, more and more people are going hungry with approximately one in three people suffering from moderate to severe levels of food insecurity (FAO et al., 2021). World hunger increased during the COVID-19 pandemic by 320 million people in 2020; this surge is equal to the total increase from the last five years combined (FAO et al., 2021). Out of the total number of undernourished, over one-third live in least-developed countries (LDC), where food security is a major issue (FAO et al., 2021). Although least developed countries (LDCs) make up just 14% of the world's population, they comprise more than 30% of the world's undernourished, demonstrating a clear correlation between low levels of economic development and food insecurity (FAO, 2021a). To meet increasing food demand and help those suffering from insufficient access to food, it is more important than ever to increase agricultural productivity.

Nepal is the poorest country in South Asia and although it has made progress in terms of development, it is still among the least developed nations in the world. The majority of Nepal's population is reliant on the agricultural sector for their livelihoods, and about one-quarter of the population lives below the poverty line (World Bank Group, 2021a). The topography in Nepal is divided into three distinctive regions: the southern Terai, the central Hills, and the northern Mountains (i.e., the Himalayas), with approximately 29% of total land used for agricultural purposes (FAO, 2021b; GON Ministry of Health and Population (MOHP) et al., 2012). The Terai region, with its flat, tropical climate, provides the most fertile lands for cultivating cereals, vegetables, wheat, maize, and rice (Sharma, 2001). The Hill region has a wide-range of agro-ecological variation that allows farmers to produce vegetables in both the normal season and the rainy season, which is considered the “off-season” for Terai farmers (USAID, 2011). The steep and rough terrain of the mountainous Himalayan region forces farmers to rely on livestock and livestock products for most of their agricultural income. Still, farmers can produce one crop, typically potatoes or temperate fruits, a year in favorable weather conditions. Despite Nepal’s agricultural potential, population growth has surpassed agricultural output in recent years creating a food deficit that cannot keep up with demand (World Bank Group, 2021a).

Figure 1.1 Map of Nepal



(Joshi et al, 2018)

A key constraint limiting Nepal’s agricultural potential and productivity are native and invasive insect species that can devastate farmers' yields, adversely affecting farm households' food security and livelihoods. In Nepal, some of the major insects pests include the tomato leaf-miner (*Tuta absoluta),* tobacco caterpillar *(Spodoptera litura),* and red pumpkin beetle (*Aulacophora foveicollis)* (CABI, 2021). Recently, the arrival of the fall armyworm (*Spodoptera frugiperda)* has raised serious concerns for Nepali farmers (Norton, 2020). The fall armyworm (FAW) is an invasive plant pest, native to the Americas, that has spread across the African continent causing up to 3 billion dollars’ worth of damage since 2016 (Goergen et al., 2016). Although the fall armyworm was suspected to have arrived in Nepal in May 2019, the Nepali government officially announced the pests' invasion on August 12, 2019 (National Plant Protection Organization (NPPO) Nepal, 2019). Fall armyworm larvae damage crops by consuming its foliage. One study found that FAW damage during corn's late-vegetative stage reduced farmers' yields by 5% to 20% (Marenco et al., 1992). The pest's ability to spread rapidly across a geographic region, resistance to many conventional pesticides, and its affinity for maize, a key staple food in Nepal, make fall armyworm a very dangerous and potentially devastating threat (Goergen et al., 2016)

Rising population and increased demand for food combined with the ability of native and invasive pests to reduce crop yields have caused farmers, eager to protect their crops and livelihoods, to turn to conventional synthetic pesticides. Pesticides, which include herbicides, insecticides, and fungicides, are used by farmers to rid and protect crops from invasion of insect pests, plant pathogens, and weeds (Fernandez-Cornejo et al., 2014). The use of conventional synthetic pesticides in South Asia farming originated in India in 1952 and has been steadily growing ever since (Aktar et al., 2009). In the 1970's, "The Green Revolution" introduced synthetic pesticides to developing counties as part of its technological paradigm to increase food production (Norton, Alwang, Kassie, et al., 2019). Pesticides (e.g., DDT and BHC) were first introduced in Nepal in 1995 (Diwakar et al., 2010). Since then, Nepali farmers have become increasingly dependent on a variety of synthetic pesticides. A study in 2018 found that 80% of the Nepali farmers surveyed used synthetic pesticides as their sole means to control pest populations (Rijal et al., 2018).

While useful in protecting crop yields, synthetic pesticides' toxic properties raise serious concerns in terms of both health and environmental hazards. The groups that have the most direct interaction with pesticides' toxicity are production workers, sprayers, mixers, formulators, loaders, and agricultural farm workers (Aktar et al., 2009). In terms of human health, synthetic pesticides enter the body during the application process, either through breathing, swallowing, or skin absorption. The resulting damage varies based on the individual's relative healthiness (Rapisarda et al., 2017). Various studies on these health effects have linked exposure to short-term effects (e.g., stinging eyes, rashes, blisters, nausea, and dizziness) and long-term conditions (e.g., asthma, neuropathy, and cancer) (US EPA, 2013).

Another adverse consequence of synthetic pesticide use is that pesticides can harm or kill beneficial insects, fish, birds, non-target plants, and other organisms (Sexton et al., 2007). Synthetic pesticides can contaminate surface and groundwater, as well as turf and other vegetation, which is both costly and time-consuming to remove. Spraying pesticides can cause unintended effects such as hitting non-target vegetables and chemicals drifting from the target region, possibly spreading over several hundred yards (Sexton et al., 2007). In addition to these health and environmental effects, another concern is that using pesticides can create a vicious cycle of dependency. As synthetic pesticide use increases, pests mutate to become more resilient, requiring an ever-increasing higher dosage of pesticides to maintain the same level of effectiveness (Sexton et al., 2007).

As the unintended consequences of synthetic pesticide use have become more apparent, Integrated pest management (IPM) strategies have been initiated (Morse & Buhler, 1997). IPM is an arguably cheaper and less harmful alternative to conventional synthetic pesticides and is a way of managing and preventing agricultural pests using different levels of control methods (e.g., biological, cultural, and chemical) that have minimal adverse environmental and human health impacts (Norton, Alwang, Kassie, et al., 2019). Pest management practices include weeding, removing diseased plants or harmful insects, using beneficial insects, and using pest-resistant seeds. Benefits from adopting IPM practices to the individual farmer include increased yields, reduced pesticide expenses, and increased incomes (Norton, Alwang, Kassie, et al., 2019).

Integrated pest management practices were launched in Nepal in 1997 after farmers experienced the devastating effects of an invasive plant species called the brown planthopper (*Nilaparvata lugens Stal)* (L. Kafle et al., 2014). Since then, the Government of Nepal (GON) has supported IPM programs. However, IPM is not widely adopted by Nepali farmers. A 2018 survey found that just 34% of farmers knew what IPM was, and only 14 percent of farmers were adopting IPM practices in some form (Rijal et al., 2018). This could be due to several factors such as access to agricultural extension offices, not enough evidence on the costs and benefits of using IPM technologies, farmer risk aversion, or lack of knowledge on negative pesticide effects (L. Kafle et al., 2014; Knaresboro, 2019; Norton, Alwang, & Larochelle, 2019)

The Feed the Future (FTF) Innovation Lab for Integrated Pest Management is a USAID-led program that has been in place for 15 years and focuses on tackling poverty, hunger, and undernutrition in various developing countries by increasing the adoption of IPM practices. The FTF strategy in Nepal is to: (1) promote value chain growth and diversification, (2) increase incomes, (3) enhance food security, (4) increase resilience to climatic and economic shocks and stressors, and (5) improve nutritional status of women and children (Feed the Future, 2021). Some of its successes include 172,000 producers using new technologies and practices and reducing the prevalence of poverty by 35% since 2011 in the targeted areas (Feed the Future, 2021). Although great work has been carried out to date, to further expand the use of IPM practices in Nepal, there needs to be more information available to farmers on the benefits and costs of IPM practices. This research project seeks to identify the factors impacting the adoption of IPM practices and build evidence on the economic benefits of IPM. Understanding the factors that impact IPM adoption can help the Government of Nepal, FTF program officials, and other stakeholders better tailor IPM education and training programs. Information on the costs and benefits of different pest management strategies can help Nepali farmers make more informed decisions on their pest management practices.

1.2 Objectives of the Study

This study analyzes vegetable IPM practices being employed by Nepali farmers. Specific objectives of this project are to:

1. Determine the extent of adoption of IPM practices and assess the factors (e.g., age, gender, distance to agricultural extension offices, education, experience, training in IPM, sources of agricultural knowledge) that affect Nepali farmers' decision to adopt various IPM practices for specific high-value vegetables (tomato, cauliflower, onion, and cucumber).
2. Compare the economic benefits of IPM practices on target crops (tomato, cauliflower, onion, and cucumber) to other more conventional pest management practices.

1.3 Organization of Thesis

This thesis is divided into six chapters. Chapter 1 introduced the thesis, and Chapter 2 provides background information on Nepal and pest management practices. Chapter 3 presents the conceptual framework on IPM adoption and the methodology used in this study. Chapter 4 focuses on economic impact assessments and includes a literature review, theoretical background, methodology, and summary of data. Chapter 5 presents the results from the estimation of models discussed in Chapter 3 and Chapter 4. Chapter 6 concludes with a summary, suggestions for future research projects, policy implications, and study limitations.

Chapter 2. Background on Nepal

This chapter provides background information relevant to this study, including Nepal's 1) economy and current state of development, 2) social structure (i.e., caste system, indigenous peoples, and gender), 3) vegetable production, 4) vegetable pests, and 5) pest prevention and control.

2.1 Nepal's Economy and Current State of Development

Nepal is a developing country landlocked between China and India in South Asia. The country's population of 30 million is composed mainly of young people (GON Central Bureau of Statistics, 2021b). However, the population pyramid is changing as the number of children under the age of 14 has started to decline (World Bank Group, 2021a). Based on data and historical trends, Nepal is currently in the midst of a demographic transition from a mainly agricultural nation with high fertility and mortality rates to a more urbanized society with lower fertility and mortality rates (Stage II approaching Stage III) (GON National Planning Commission & UNICEF, 2017; United Nations Population Fund, 2017). Life expectancy has drastically increased from 41 years in 1980 to 71 years in 2019 (United Nations, 2019). Investments in health and improved access to quality reproductive services have fueled this transition and helped decrease both birth and infant mortality rates (United Nations Population Fund, 2017).

With most adults working in agriculture, Nepal is an agrarian society (International Labor Organization, 2021). However, the services sector comprises the largest share of the country's gross domestic product (GDP) (World Bank Group, 2021a). In the past, the fastest-growing sector was industry, but the agricultural sector had the highest growth rate in 2020 (World Bank Group, 2021a). In the manufacturing sector, food and beverages make up the largest share (over one-third) of total manufacturing GDP. (GON Department of Customs, 2018).

In the global market, Nepal's strongest economic ties are with neighboring India. India is Nepal's primary trading partner, accounting for almost two-thirds of Nepal's total trade (GON Department of Customs, 2018). Nepal's top exports are textiles and clothing, which made up over 40% of total exports in 2017 (GON Central Bureau of Statistics, 2021a). Almost all of Nepal's exports depend on imported inputs (GON Department of Customs, 2018). Nepal's largest import products are machinery, fuel, metal, transportation equipment, and food products (GON Department of Customs, 2018). Although Nepal has experienced chronic trade deficits, the trade deficit has risen sharply in the last five years due to increasing domestic consumer demand (GON Department of Customs, 2018).

Lack of economic opportunities within Nepal has led a large portion of the workforce to seek employment in nearby countries such as India, Qatar, and Malaysia (International Labor Organization, 2020). This large-scale migration drains Nepal's human resource base and creates a shortage of domestic skilled labor. Nepal's economy is heavily dependent on wages sent home from migrant Nepali workers, known as *remittances*, which comprise roughly one-fourth of the country's total GDP (World Bank Group, 2021a). Remittances have mixed economic impacts. Although remittances can help increase incomes and consumption, this rise in consumption can appreciate the real exchange rate, which in turn favors imports and hampers exports resulting in increased trade deficits (World Bank Group, 2021b).

Nepal's education system has improved but still struggles with high dropout and repetition rates (GON Ministry of Education et al., 2016). Dropout rates are worse in rural areas, where children from poor farm households leave school to help with farm work (GON Ministry of Education et al., 2016). While female participation in education has improved, female literacy rates still lag behind those of males (UNESCO Institute for Statistics (UIS), 2018).

In terms of poverty alleviation, gross national income (GNI) per capita (PPP in current international $) has increased over time and is currently $4,060 (World Bank Group, 2021a). In addition, the World Bank reports that the percentage of people living on less than $1.90 a day (in 2011 PPP) decreased from 50% of the population in 2003 to 15% in 2010 (World Bank Group, 2021a). Income inequality has decreased over time, but it is still a persistent issue since the top quintile (i.e., top 20% of earners) receives 41.5% of income and the lowest quintile holds only 8.3% (World Bank Group, 2021a).

2.1.1 COVID-19 Impacts

Nepal encountered its first confirmed case of the COVID-19 virus in late January of 2020 (International Monetary Fund, 2021a). Cases continued to rise until the country imposed a nationwide lockdown in March 2020 that lasted until July 2020 (International Monetary Fund, 2021a; World Bank Group, 2021b). As of mid-August 2021, Nepal has had 748,981 COVID cases and 10,533 COVID-related deaths (GON Epidemiology and Disease Control Division, 2021). Vaccine rollout has been slow with only 16% of the population who have received at least one dose of the COVID-19 vaccine (Ritchie et al., 2021). In comparison, 58% of high-income, 39% of upper-middle-income, 21% of low-middle-income, and 1% of low-income countries have received at least one dose of the COVID-19 vaccine (Ritchie et al., 2021).

Because of the COVID-19 pandemic, Nepal experienced its first economic contraction (reduction of real GDP by 1.9%) in 40 years (World Bank Group, 2021b). While the services and industry sectors were hit hard, the agricultural sector expanded by 2.2% despite disruptions to farm inputs and market access (World Bank Group, 2021b). In terms of individuals, migrant workers, women, and children have been disproportionately affected by the economic downturn (GON National Planning Commission, 2020).

In response to the COVID-19 crisis, the Government of Nepal introduced several support packages to compensate businesses for labor costs, help affected economic sectors, support small businesses and self-employed, and provide unemployment compensation (International Monetary Fund, 2021a).

2.2 Social Structure

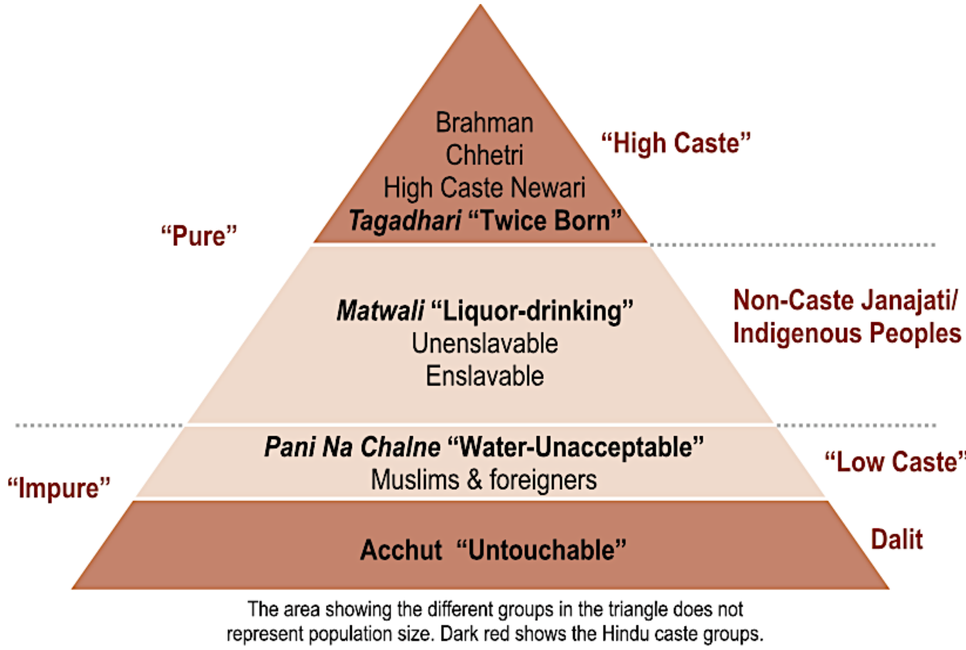
Along with Nepal's geographic variety, it has a diverse population with different cultures, religions, dialects, and ethnicities. According to the 2011 Census, there are 126 distinct caste and ethnic groups in Nepal (GON Central Bureau of Statistics (CBS), 2014). The major caste and ethnic groups are the high-caste Hindus, low-caste Hindus (e.g., Dalits), indigenous peoples (or *Adivasi Janjatis)*, and the Madhesi people who make up different caste and ethnic groups in the Terai region (Hangen, 2007).

2.2.1 Religion and Caste System

While there are ten types of religions reported in Nepal, Hinduism is the most popular, making up 80% of the population (GON Central Bureau of Statistics (CBS), 2014). Buddhism is the second most popular belief practiced by 10% of the population (GON Central Bureau of Statistics (CBS), 2014).

Nepal's caste system dates back to the late 14th century (Bennett et al., 2008). During the reign of King Jayasthiti Malla (1380 – 1394), he divided people into 64 hereditary classes, or *castes*, based on their occupation (Bennett et al., 2008). This system was in place for several hundred years until the 19th century. Established in 1854, the *Muluki Ain* (National Code of Nepal) separated the 64 caste groups into four hierarchies (Höfer, 2004).

Figure 2.1 Nepal's Caste Pyramid



(The World Bank & DFID Nepal, 2006)

The hierarchies, shown in Figure 2.1, are 1) *Tagadhari* who were considered pure and could wear sacred thread, 2) *Matwali* or alcohol drinkers, 3) *Pani Na Chaine* who were considered impure but touchable, and 4) *Acchut* who were considered impure and untouchable (Subedi, 2011; The World Bank & DFID Nepal, 2006). Although the caste system is commonly believed to originate from Hindu beliefs, hereditary informal and formal systems that cause social stratification are present in all parts of the world (Subedi, 2011). Discrimination based on a person's caste has been illegal since 1963, but the caste system and the inequality that accompanies it are still very present in Nepal (The World Bank & DFID Nepal, 2006). A 2008 study on the ethnic and caste stratification in Nepal found that, "for most people living in the territorial boundaries of the modern Nepali state – especially after the promulgation of the National Code or *Muluki Ain* in 1854 – the caste system has been a major determinant of their identity, social status and life chances" (Bennett et al., 2008, p. 1).

Today, the high-caste Hindus (Brahmans and Chhetris) and high-caste Newars have a dominant presence in political positions, higher health indicators, and lower poverty levels (Hangen, 2007; The World Bank & DFID Nepal, 2006). The lower caste and ethnic groups (Dalits and Muslims) have higher poverty incidence, lower health indicators, and lower educational attainment (The World Bank & DFID Nepal, 2006). A 2006 assessment on the relationship between Nepal's gender, caste, and ethnicity institutions and social exclusion reports that Dalits are at the bottom of Nepal's caste hierarchy, with very little representation in public service jobs or government positions (The World Bank & DFID Nepal, 2006). There is a geographic dimension to caste and ethnic group inequality, with Hill groups generally having higher Human Development Indicator (HDI) scores than their Terai counterparts (Nepal & United Nations Development Programme (Nepal), 2014). Human Development Indicators include life expectancy at birth, expected and mean years of schooling, and GNI per capita (PPP $) (UNDP, 2021).

2.2.2 Indigenous peoples

In 2002, the Government of Nepal defined indigenous peoples as "a tribe or community having its own mother language and traditional rites and customs, distinct cultural identity, distinct social structure, and written or unwritten history" (National Foundation for Upliftment of Aadibasi/Janjati Act, 2002). Nepal's 59 recognized indigenous groups or "Janajatis" are spread out across the country: 18 in the Mountains; 24 in the Hills; and 17 in the Terai (GON Ministry of Law, Justice and Parliamentary Affairs., 2002). Newars are a Nepali indigenous nationality, but they are often regarded as a separate group because of their high socioeconomic status (Hangen, 2007).

In addition to economic, gender, and political exclusion, a significant portion of Nepal's population also face cultural exclusion. The Constitution declares Nepal a Hindu kingdom and Nepali as the only official language, which excludes non-Hindus and the languages spoken by Janajatis (who make up almost 40% of the country's population) and other linguistic minority groups (Bhattachan, 2012; The World Bank & DFID Nepal, 2006). Hangen (2007) argues that "Ethnic inequality has been a persistent and pervasive feature of the modern state, even though it was not widely discussed or acknowledged until the 1990s" and points out disparities in access to Nepali government resources and political power (Hangen, 2007, p. 7).

2.2.3 Gender

Over the past 30 years, Nepal has made significant progress towards closing the gender parity gap. Compared to 1995, women have greater levels of educational achievement, representation in politics, access to education, maternal and child health services, and economic resources and opportunities (Pudasaini et al., 2015). The government has aided in this advancement by adopting more gender-friendly laws and attempting to amend previous discriminatory rulings (Pudasaini et al., 2015). Although there have been significant strides in promoting gender equality and women's empowerment, Nepali women continue to lag behind men in social, political, and economic spheres (Pudasaini et al., 2015).

In the political sphere, discriminatory inheritance and citizenship laws continue to exist. The affirmative action policies lack institutional support in terms of funding and personnel (Pudasaini et al., 2015). With over 80% of economically active women working in agriculture, women are a fundamental part of Nepal's agricultural sector (FAO, 2019). However, only a small percentage (16%) of women have ownership and title to land (Dhakal, 2011). In addition, only 21% of men work as unpaid labor on household farms, compared to 60% of women (The World Bank & DFID Nepal, 2006).

Women continue to face wage discrimination and trouble accessing capital, credit, and technical training required to better participate in economic markets (Pudasaini et al., 2015). As a result, although Nepal has made progress to be more inclusive and gender-friendly, the country remains a patriarchal society with restrictive gender stereotypes that paint women as weak and inferior (Pudasaini et al., 2015).

2.3 Vegetable Production in Nepal

Comprising 9.7% of Nepal's GDP, vegetable production is an important part of Nepal's economy (CASA Nepal, 2020). As consumer demand and consumption of vegetables have increased, so has productivity and total production (CASA Nepal, 2020). Nepal's distinct ecosystem and topography allows for the farming of over 200 different vegetable species including onions, tomatoes, cabbages, cauliflowers, French beans, cucumbers, and chili peppers (USAID, 2011). The Terai region is the most productive in vegetable farming but is closely followed by the Hills (Bhandari et al., 2016). However, unlike the Terai, the Hill region's higher altitude allows for vegetable farming during the rainy or "off" season. During the off-season, Hill farmers benefit from higher prices in the Terai markets for these scarcer, high-value crops. The vegetables that this study focuses on are tomato, cauliflower, onion, and cucumber.

2.3.1 Tomato Production

The tomato, rich in nutrients and flavor, is one of the most consumed vegetables in Nepal. Because of its high yield and profit value, tomatoes are also a popular crop for farmers (Bhandari et al., 2016). Nepal's varying climate allows for the year-round production of tomatoes (Bhandari et al., 2016). The farming methods to produce tomatoes are either in an open field (possibly in a plastic tunnel) or in a net house (i.e., an enclosed structure with agro-nets). Since tomatoes are sensitive to environmental conditions, off-season Hill farmers often use plastic tunnels (i.e., a semi-enclosed structure of bamboo sticks or iron poles covered with a plastic sheet(s)) to regulate temperature and excess rainwater (FAO, 2013). Because farmers modify these tunnels based on the size and shape of their farms, production costs vary (Kc et al., 2021). Other production costs for Nepali tomato farmers are seeds, fertilizer, compost, staking poles, pesticides, and labor (Pokhrel, 2010).

Tomatoes require specific growing conditions, so instead of planting seeds directly in the field, tomato seedlings are grown initially in seedbeds or greenhouses and then transplanted to the field after 5 to 6 weeks (Kelly & Boyhan, 2006). After transplantation, tomato seedlings typically are covered by plastic mulch on raised beds to drain excess water and provide heat for this warm-season crop (Kelly & Boyhan, 2006).

2.3.2 Cauliflower Production

The cauliflower plant is part of the *Brassicaceae* family, making it closely related to other cruciferous vegetables (e.g., cabbage and broccoli) (Petruzzello, 2019). The edible head or curd of the plant is a regular ingredient in many Nepali meals. Cauliflower is a cool-season crop; grown best in fertile soil, cauliflower can grow to a height of 1.5 feet (Petruzzello, 2019). In 2015, cruciferous vegetables made up over one-third of total vegetable production in Nepal (GON Ministry of Agricultural Development & Agri-Business Promotion and Statistics Division, 2016).

In terms of cultivated area and production volume, cauliflower is the most popular vegetable for Nepali farmers to grow (CASA Nepal, 2020). The biggest production costs for cauliflower are compost, fertilizer, workers (including family labor), seeds, and pesticides (Pokhrel, 2010)

2.3.3 Onion Production

Onions, native to southwest Asia, are a flavorful cooking addition to many Nepali meals. The edible bulb of an onion can be processed in many different ways. It is a biennial plant, which means it has two growing periods. In the first period, these plants produce their roots, stems, and leaves; in the second period, onions produce fruits and flowers (The Editors of Encyclopaedia Britannica, 2020). A 2018 analysis on Nepali onion production found that most onion farmers in the Terai region use seeds imported from India (Timsina & Shivakoti, 2018). The main production costs for Nepali onion farmers are labor (for land preparation and intercultural operations) and compost. Currently, Nepal imports a significant amount of vegetables, especially onions, but increasing domestic off-season onion production in the Hills could help ease this reliance (USAID, 2011).

2.3.4 Cucumber Production

Cucumbers are part of the *Cucurbitaceae* family and are a common vegetable grown by Nepali farmers (Orzolek et al., 2010). Some plants have root systems that are delicate or spread out so they can be planted directly into the soil, a process that is called direct seeding or direct sowing. In Nepal, cucumber farmers practice both direct sowing and transplanting. Cucumbers are sensitive to cold temperatures, so Hill farmers will use a plastic tunnel to protect seedlings during the winter. Cucumbers grow best in deep, fertile soil that is not overly acidic (FDA & WIFSS, 2016). The main production costs for Nepali cucumber farmers are workers (including family labor), compost, and pesticides (Pokhrel, 2010). Like all vegetables, cucumbers are vulnerable to different pests and require continuous monitoring and management to grow.

2.4 Vegetable Insect Pests and Diseases

2.4.1 Insect and non-insect pests

Insects are organisms that belong to the *Arthropoda* phyla and the *Insecta* class (Burrack & Bertone, 2018). To be considered an insect, an arthropod must have three body segments and three pairs of legs (Burrack & Bertone, 2018). Although most insects are benign or even beneficial, a small portion of insects are pests that disrupt and threaten a plant's survival (Burrack & Bertone, 2018). Pests are either native or invasive. Native pest species occupy an area naturally (i.e., without an introduction) (Species Survival Commission, 2000). A species is "non-native" if it is not previously known to the geographical area, and a species is "invasive" if it is non-native and causes more negative than beneficial effects (Beck et al., 2008). Native and invasive pests can cause partial damage to complete destruction of crops, devastating a farmer's yield and source of income. Subsistence farming (i.e., farming to meet the needs of the farm household) is common in Nepal, so pest destruction can induce food insecurity for small-scale Nepali farm-households.

In our 2021 survey (discussed in Chapter 3), we asked Nepali farmers which type of pest (e.g., insects/worms, diseases/viruses, weeds, birds, and rodents) caused the most damage to their crop in the last growing year. The majority of tomato, cauliflower, and cucumber farmers answered that insects/worms caused the most damage to their crops. For onion farmers, insects/worms and diseases/viruses were the worst types of pests.

Tomato Insects—

From the pest incidence data we collected in our survey, the worst insect for Nepali tomato farmers in our study area is tomato fruit borers, a moth species whose larvae feed on fruit's seeds and flesh (Purdue University, 2013). In particular, the most damaging and persistent type of fruit borer is *Tuta absoluta.*

Figure 2.2 Tuta Absoluta
©Marja van der Straten, NVWA Plant Protection Service

Tuta absoluta (Figure 2.2) is an invasive pest that has caused major problems for tomato farmers by feeding on the leaves, buds, stems, and fruits of tomatoes and other solanaceous crops (Bajracharya et al., 2016; van der Straten, 2011). Native to South America, this pest is alternatively known as the "South American leaf-miner". Evidence from a commercial tomato farm in Kathmandu indicates that the South American leaf-miner first invaded Nepal in 2016 (Bajracharya et al., 2016b). This pest was most likely introduced into Nepal through vegetables imported from India, demonstrating how Nepal's reliance on foreign vegetables makes the country particularly vulnerable to pests and other pathogens that can travel during importation (Shashank et al., 2015; Venkatramanan et al., 2019). Using a partial equilibrium approach, Venkatramanan et al. (2019) estimated that the pest's invasion into Nepal could cause upward of $24 million in damages.

Cauliflower Insects—

For Nepali cauliflower farmers, the most persistent (year-round) pest is the tobacco caterpillar, which makes a downward hole into the cauliflower head to feed (Ghimire et al., 2010). Other major insect pests for cauliflower farmers are aphids (small, soft-bodied insects) and cabbage butterflies, which both feed on the leaves of cauliflower plants, causing deformed leaves, wilting, and stunting (Ghimire et al., 2010; Sparks, 2006).

Onion Insects—

For onion farmers, the worst insect pest is thrips. Thrips are very small (1-2 mm) insects that feed on the emerging leaves of onion plants, causing red, gray, or silver spotted discoloration (Sparks, 2006). Thrips can persist throughout a plant's life cycle by feeding and reproducing on foliage (Sparks, 2006).

Cucumber Insects—

The most damaging insects for Nepali cucumber farmers are fruit flies, red pumpkin beetles, and spotted cucumber beetles. Fruit flies, commonly regarded as the worst cucurbit pest in Nepal, damage crops (as maggots and fully grown adults) from March to September (K. R. Kafle, 2021). Red pumpkin and spotted cucumber beetles, both serious carriers of diseases and viruses, feed on cucumber leaves, roots, and stems, damaging the vegetable in the process (Hossain & Rafiquzzaman, 2021; University of Maryland Extension, 2021). Spotted cucumber beetle larvae are also called “rindworms” because they feed on the cucumber’s surface (University of Maryland Extension, 2021).

2.4.2 Plant diseases

Just as vegetables are affected by invasive and native insect pests, they are also vulnerable to plant diseases. Plant diseases are either abiotic or biotic. Poor farming practices or environmental conditions cause abiotic plant diseases (UC Statewide IPM Program, 2019). Biotic (i.e., infectious) diseases are caused by pathogens, which include organisms such as fungi, bacteria, nematodes, and viruses (Munster, 2018; UC Statewide IPM Program, 2019). Viruses are transmitted mechanically on infected surfaces or more often through vectors, which are living organisms like insects that can spread viruses (Munster, 2018).

Tomato Diseases—

The most destructive disease or virus for Nepali tomato farmers is blight (early and late). Late blight is a disease caused by water molds (similar to fungi) that spreads in cool, damp weather (Johnson et al., 2016). In contrast, early blight is caused by two fungi (*Alternaria tomatophila* and *Alternaria solan)* and prefers warmer temperatures (Johnson et al., 2018). Both types of blight cause dark brown, round spots that cover the fruit, stems, and leaves. Tomato farmers also identified the tomato yellow leaf curl virus, which causes leaves to turn yellow and curl, as a harmful pest (CABI, 2021).

Cauliflower Diseases—

The worst diseases and viruses for Nepali cauliflower farmers are clubroot (year-round), *Alternaria* leaf spot or blight (winter and summer), damping-off (spring), and downy mildew (year-round). Clubroot is a disease affecting crucifers and can cause wilting, stunting, and swollen roots that are club-shaped (Grabowski, 2018b). *Alternaria* leaf blight and downy mildew both cause brown spots on the upper surface of leaves and thrive in warm, humid conditions (Grabowski, 2018b). Damping-off, caused by fungus or mold, makes seedling stems and leaves appear water-soaked and thin, and causes roots to be stunted, with gray-brown sunken spots (Grabowski, 2018b).

Onion Diseases—

The worst disease for Nepali onion farmers is purple blotch, which is caused by the fungus *Alternaria porri* (Madeiras, 2015). This disease is most prevalent in warm and humid regions but can last through winter on nearby soil or crop remains. As shown in Figure 2.3, this disease can be identified by water-soaked lesions on onion bulbs or leaves that turn purple and black as the disease progresses (Madeiras, 2015)

Another significant disease for onion farmers is onion smut, which affects and kills seedlings (CABI, 2021).

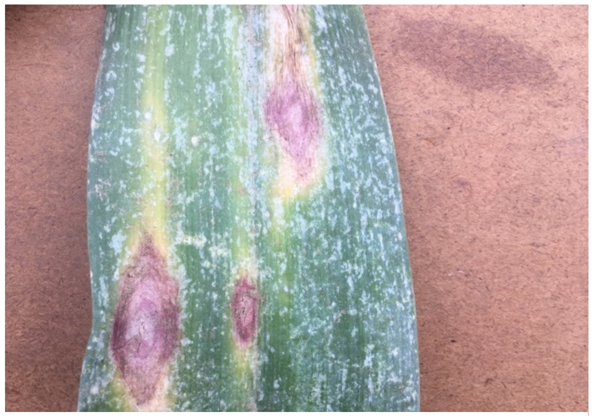


Figure 2.3 Purple Blotch of Onion
©G. Higgins, University of Massachusetts Amherst

Cucumber Diseases—

Out of several cucumber diseases and viruses, the most damaging for Nepali cucumber famers are downy and powdery mildew. Damping-off is another disease that harms cucumbers and is caused by pathogens that live and feed on dead organic matter in the soil (Perry, 2006). Young plants (i.e., seedlings) are especially vulnerable to this disease that can stunt, rot, or kill the seedlings before or after they have emerged from soil (Meadows et al., 2017). Farmers that grew winter cucumber crops were particularly affected by this disease, which reflect the fact that the pathogens thrives in cool, moist temperatures (Grabowski, 2018a). Figure 2.4 displays a cucumber with this type of disease damage.

Figure 2.4 Damping-off, blight, and rot of Cucumber

©Jason Brock, University of Georgia

2.5 Pest Prevention and Control in Nepal

2.5.1 Current Control Methods

Farmers use pesticides to rid and protect their crops from plant pests. A pesticide is an organism or substance "intended for preventing, destroying, repelling, or mitigating any pest" (NPIC, 2021, paragraph 1). Pesticides are classified by the ingredients they consist of such as conventional chemical pesticides, which are generally produced synthetically, and biopesticides, which are made of natural materials (e.g., animals, plants, bacteria) (US EPA, 2021). When studies describe the harmful effects of pesticides, they are referring to the effects of conventional synthetic pesticides.

Within both groups, pesticides are classified by the type of pests they control for including insecticides (for insects), herbicides (for weeds), fungicides (for fungi), nematicides (for nematode worms), and rodenticides (for rodents) (Nehring et al., 2014). Out of the farmers we surveyed, 86% applied conventional synthetic pesticides in the past year. In addition, over 80% of farmers answered that they choose when to apply pesticides based on visible damage and the number of pests.

In addition to the cost of purchasing and applying synthetic pesticides for individual farmers, pesticides' toxic properties create societal costs by damaging the environment and human health (Nehring et al., 2014). The agricultural groups that have the highest risks are those with the most direct interaction with pesticide toxicity and include those involved in the preparation, mixing, and application stages (Bolognesi, 2003). In terms of human health, synthetic pesticides enter the body during the application process through breathing, swallowing, or skin absorption, and the resulting damage varies based on the individual and their relative healthiness (Gaikwad et al., 2015). Various studies on pesticide exposure and health impacts have linked exposure to short-term effects of stinging eyes, rashes, blisters, nausea, and dizziness, and more long-term conditions like asthma, skin disease, neuropathy, and cancer (Roberts & Reigart, 2013). In our survey, 17% of Nepali farmers said that either they or their family members became ill from applying synthetic pesticides.

Another adverse consequence of synthetic pesticide use is that in addition to killing the targeted pest, pesticides can harm or kill beneficial insects, fish, birds, non-target plants, and other organisms. After or during the application, synthetic pesticides can travel from the target region by aerial drift, soil percolation, or surface runoff, polluting the air and contaminating groundwater in the process (Sexton et al., 2007). This environmental damage can reduce biodiversity, soil, and land conditions and cause irreversible disruption to ecosystems (Sexton et al., 2007). In addition to societal damage, frequent synthetic pesticide use can cause pests to become resistant and farmers to increase their applications, creating a vicious cycle of dependency. *Silent Spring*, written by Rachel Carson in 1962, was instrumental in introducing the public to these risks and igniting the environmental movement that demanded the agriculture industry to discover more sustainable pest management solutions (Sexton et al., 2007).

Integrated pest management (IPM) is a continuum of pest control strategies that aim to sustainably prevent and manage pest incidence and reduce reliance on conventional synthetic pesticides (Maredia, 2003). IPM came into existence in the 1960s after the unintended consequences of synthetic pesticide use became apparent (Morse & Buhler, 1997). An important aspect of IPM is the rigorous monitoring of vegetables to identify pest populations. Early IPM programs emphasized this and using synthetic pesticides only as a last resort when pest damage exceeds the monetary and social costs of pesticide applications (Sexton et al., 2007). Over time, IPM has evolved with technological improvement to include biological control agents, pest-resistance plant varieties, and cultural methods to prevent and manage pest populations (Norton, Alwang, Kassie, et al., 2019). Cultural pest management methods include soil preparation, crop rotation, hand-weeding, and removing infected plants (Norton, Alwang, Kassie, et al., 2019). Biological control is the introduction of a non-native organism to an area to decrease the density of a pest population (DeBach, 1964). Direct manipulation to the natural enemy populations (augmentation control) or their environment (conservation control) to increase their effectiveness as natural enemies are other forms of biological control (O'Neil et al., 2003). IPM also emphasizes the use of biopesticides (natural sources) over synthetic pesticides.

Biopesticides are classified into three groups: 1) biochemical pesticides, 2) plant-incorporated protectants (PIPs), and 3) microbial pesticides (US EPA, 2021). Neem products (Azadirachtin-based and neem oil) are biochemical pesticides derived from the neem tree, *Azadiracta indica,* and used by farmers as insecticides and fungicides (Caldwell et al., 2013; US EPA, 2021). Plant-incorporated protectants (PIPs) are pesticidal substances produced by genetically-modified plants (US EPA, 2021). Microbial pesticides contain a microorganism (e.g., bacterium, fungus, or virus) as the active ingredient (US EPA, 2021). Farmers use microbial pesticides from the *Trichoderma* and *Pseudomonas* species to suppress plant diseases (Caldwell et al., 2013). Farmers use other microbial pesticides such as *Bacillus Thuringiensis* (Bt), nuclear polyhedrosis virus (NPV), *Beauveria bassiana,* and *Metarhizium anisopliae* to kill insects (Caldwell et al., 2013; Gomez & Thivant, 2015). An example of a typical IPM package recommended to a vegetable farmer is presented below (Heinrichs & Muniappan, 2016).

Figure 2.5 IPM Package

Vegetable IPM Package:

1. Solarization of seedbeds and fields for the control of weeds, nematodes, and certain pathogens.
2. Incorporating compost treated with *Trichoderma* in the soil, applying neem cake to control nematodes, and the use of vesicular-arbuscular mycorrhiza (VAM) to improve the uptake of nutrients.
3. Selecting seeds of high-yielding, locally preferred, and disease-resistant varieties and treating them with *Trichoderma spp*., *Pseudomonas fluorescens*, and *Bacillus subtilis*.
4. Raising healthy seedlings using plastic trays and coco-peat and protecting seedlings from insect pests by covering them with screens and netting.
5. Rogueing of disease-infected seedlings in the nursery and the field and controlling insect pests such as thrips that pass through the netting with biopesticides.
6. Grafting scions of desired varieties on disease-resistant rootstock, especially for tomato and eggplants to overcome bacterial wilt disease.
7. Mulching fields to conserve moisture and staking to prevent fruits from touching the soil in vegetable crops.
8. Adoption of augmentative, classical, and conservation biological controls
9. Use of pheromone traps to monitor pests and the application of mating disruption technologies.
10. Incorporation of other biopesticides into the system.

(Heinrichs & Muniappan, 2016)

In Nepal, pest infestation has increased in the last few years, and farmers have found it increasingly challenging to manage pest populations (Paudel et al., 2016). A 2009 survey of Nepali vegetable farmers found that most farmers are unaware of non-synthetic IPM approaches (Paudel et al., 2016). To reduce food insecurity and improve farm incomes, it is crucial to solve pest problems and integrated pest management (IPM) is an environmentally sound and effective alternative to synthetic pesticides. The next section of this study focuses on understanding the extent of IPM adoption in Nepal and developing a framework to identify factors that affect farm pest management decisions.

Chapter 3. Construction of the Adoption Model and Survey

3.1 Literature Review

When assessing the success of agricultural technologies and programs, researchers examine factors that influence adoption and widespread diffusion. An assumption in adoption literature is that farmers seek to maximize their utility (e.g., profits) subject to their budget constraints (Griliches, 1957). An adoption model typically includes household and farm characteristics as determinants of technology adoption (Feder & Umali, 1993).

A large body of literature examines the relationship between knowledge and adoption (Adesina et al., 2000; Feder & O'Mara, 1982; Foster & Rosenzweig, 1995; Jack & Tobias, 2017; Strauss, 1991). Feder and O'Mara (1982) suggest that farmers follow a Bayesian learning process, where they modify their beliefs on new technology as more information becomes available. Similarly, Adesina et al. (2000) find that farmers who have contact with extension agents are more likely to adopt a new cropping technology in Cameroon. Research also has shown that the method by which farmers receive information about a new technology impacts their choice to adopt (Mauceri et al., 2007; Myrick et al., 2014). For example, in a study on the effectiveness of different diffusion methods promoting integrated pest management (IPM) adoption in Ecuador, Mauceri et al. (2007) find that farmers who participate in farmer field schools (FFS) use more IPM practices than those that receive information about IPM practices through other diffusion methods.

There has been increased interest in understanding how health and the environment relate to farm-management decisions (Jørs et al., 2017; Rijal et al., 2018). For example, Jørs et al. (2017) find that farmers in Bolivia are aware of and concerned about pesticides' adverse effects on the environment, the health of their crops, and their own health, which influences their pest management decisions. In contrast, a 2018 study of Nepal farmers discovers that while most farmers are aware of the harmful effects of pesticides, they also use chemical pesticides as the primary method of pest infestation control on their crops (Rijal et al., 2018).

Various studies have examined how social structure affects a farmer's decision to adopt a new practice or technology (Gupta et al., 2020; Joshi, 2018). However, no study has identified whether an individual's caste or ethnic group affects their choice to adopt multiple integrated pest management practices, so this paper will address this gap in the literature.

Adoption of IPM in Low-Income Countries

Although integrated pest management (IPM) was conceptualized and first implemented in developed countries in the 1960s, IPM packages are now largely accessible to farmers in developing countries (Morse & Buhler, 1997; Norton, Alwang, & Larochelle, 2019). IPM is a continuum of practices, so IPM adoption can be defined as adopting a single practice, a combination of practices, or the degree (count) of all practices (Norton & Swinton, 2009). Studies on the adoption of IPM in low-income countries are heterogeneous in their definitions of adoption, but the consensus is that IPM practices are not widespread in the developing world (Jørs et al., 2017; Norton, Alwang, & Larochelle, 2019; Orr, 2003; Parsa et al., 2014). A common misconception is that IPM programs, created in developed countries, can easily be introduced and adopted in developing countries (Peshin & Dhawan, 2009). Low-income countries generally have lower levels of infrastructure, extension programs, information systems, and chemical pesticide enforcement or regulations (Peshin & Dhawan, 2009). In addition, farms in developing countries are generally small, markets are variable, farmers use large portions of their yield for household consumption, and cropping systems can be elaborate (e.g., intercropping) (Morse & Buhler, 1997). Furthermore, farmers in low-income countries often have greater credit and resource constraints, which can increase their risk aversion and uncertainty, making them less likely to adopt new technologies or practices (Feder, 1979; Foster & Rosenzweig, 2010).

Another obstacle to IPM adoption in developing countries is that IPM can be complex, requiring extensive ecological knowledge of pests (Jørs et al., 2017; Morse & Buhler, 1997). In addition, there is a greater emphasis in the developing world on the monetary advantages of IPM practices, which indicates the need for further evidence comparing the costs and benefits of IPM to current chemical approaches (Jørs et al., 2017; Norton, Alwang, & Larochelle, 2019; Parsa et al., 2014). Since IPM is location-specific, this research study serves to understand the factors influencing the adoption of IPM practices in **Nepal** and provide evidence of the economic benefits of IPM. This information can be used to strengthen and enhance IPM adoption programs and farmer outreach efforts and allow farmers to make more informed decisions regarding their pest management practices.

3.2 Conceptual Framework

Feder and Umali (1993) define innovation as a "technological factor that changes the production function and regarding which there exists some uncertainty, whether perceived or objective (or both)." (p. 216). As farmers increase their experience or knowledge of a technology, their uncertainty decreases over time. Additionally, when farmers become more familiar with a specific technology, they use it more efficiently, which changes the production function (Feder & Umali, 1993). This dynamic innovation diffusion process can be looked at from both the micro and macro levels (Feder & Umali, 1993).

At the micro-level, when a farmer is in the process of deciding whether or not to adopt a new agricultural technology, the basic economic theory of the consumer choice model applies

(Mills, 1997). Consistent with this theory, the famer will compare the new technology's potential utility, satisfaction, or benefits to current technology, subject to their budget or input constraints (land, credit, and labor) (Feder et al., 1985). The increase in utility or benefits from the new technology could arise from higher profits or lower health risks (Mauceri et al., 2007). Costs may be monetary values, such as fixed costs, or risk and uncertainty that accompany new technologies. Farmers use their own experiences and the experiences of others (e.g., neighbors, friends, and family members) along with previous results (e.g., cost, yield, and gross profit) to estimate a new technology's expected utility (Feder et al., 1985). Incorporating perceived risk into the expected utility optimization model, a farmer will choose to adopt the new technology if they anticipate it will provide greater benefits than current technology (Feder & Umali, 1993). Because agricultural technologies are rarely uniformly adopted, it is important to look at individual farmer characteristics that may encourage or hamper a decision to adopt a new technology. As a result, research studies often include individual farmer characteristics such as age, education, and farming experience as determinants in an adoption model.

At a macro level, researchers examine aggregate adoption in a given population to identify distinct trends that make up an effective diffusion process (Feder & Umali, 1993; Rogers, 1983). The diffusion process is the cycle in which an innovation is communicated through different channels between members of a population or social system over time (Rogers & Stanfield, 1968). Communication channels for IPM technologies include farmer field schools, field days, information and communication technologies (e.g., videos and SMS messages), or interpersonal channels (e.g., extension agents, neighbors, friends, and family members). Rogers (1983) argues that information is more likely to lead to behavior change when it is communicated between similar individuals. Similarities could be a mutual language, belief, social status, or education level (Rogers, 1983).

Our analysis primarily examines the adoption decision from a micro level. To determine the significant factors behind adoption of IPM practices by Nepali farmers from a micro level, we conducted a cross-sectional survey and analyzed the data gathered on the internal factors (e.g., age, education level, and membership in farmer organizations) and external factors (e.g., Nepal's caste system, source of IPM information, and geographic location) that are likely to affect farm-management decisions.

3.3 Survey and Adoption Data

3.3.1 Survey Construction

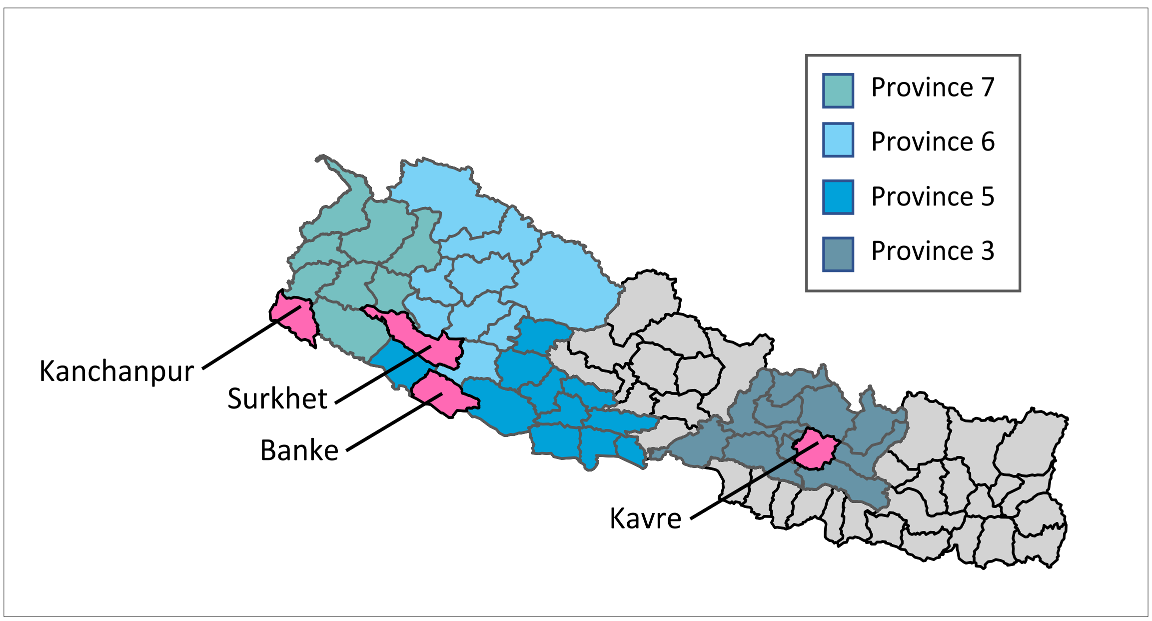
Development of the survey took place in 2020. The complete survey provided cross-sectional data on household demographics, IPM knowledge and training sources, farm characteristics, seedbed and land preparation, crop establishment, fertilizer application, pest management, and production and disposal. The last section of the survey asked farmers about the possible impacts that the COVID-19 pandemic has had on their farming activities. The survey had 15 sections that included production and pest questions separated by season (i.e., winter, spring, summer). The survey focused primarily on four vegetables (i.e., tomato, cauliflower, onion, and cucumber) but did include questions regarding pest incidence for farmers growing maize, rice, or lentils. Questions could be skipped depending on previous answers.

3.3.2 Sample design

FTFNIPM works across the USAID Zone of Influence (ZOI). The ZOI includes 25 districts within provinces 3, 5, 6, and 7, where USAID has committed to investing its resources for food security and agricultural development. The survey took place within four **districts**:

Banke, Surkhet, Kavrepalanchok, and Kanchanpur. Two districts (Banke and Surkhet) were selected because the IPM Innovation Lab (IL) had recently worked there. The other two districts (Kavrepalanchok and Kanchanpur) were selected because the IPM IL had not previously worked there. Kavrepalanchok (or Kavre) and Surkhet are located in the Hills and Banke and Kanchanpur are in the Terai region. All four districts are in the USAID's ZOI and produce significant amounts of the crops that the survey focuses on. The provinces within USAID's ZOI and the four selected districts for the survey are displayed below.

Figure 3.1 USAID's ZOI and Survey Districts



To select **municipalities**, a list of the municipalities within the four districts with significant tomato, cauliflower, onion, and cucumber production was created and ranked by the amount of production of FTFNIPM crops with the assistance of the iDE Nepal team. The top two municipalities that had the most involvement (i.e., the largest number of farmers) in tomato, cauliflower, onion, and cucumber farming from each district were selected. In total, eight municipalities were selected. To select **wards**, a list of the wards within the eight municipalities with each ward's area (km^2), population, and total number of households was obtained by iDE

Nepal. Since some municipalities had more wards than others, each ward was weighted by household size (i.e., total number of households) and selected randomly from the list of 81 wards to ensure that each household within the ward had an equal chance of being selected. Ultimately, 25 wards were selected to be surveyed.

From the 25 selected wards, publicly available lists of the villages within the wards that grow at least some of the target crops (tomato, cauliflower, onion, and cucumber) were created. After that, two villages were randomly chosen from each ward. In total, 50 villages were selected. After selecting villages, we used publicly available lists of the households in the villages to identify the households that grew at least some of the target crops of tomato, cauliflower, onion, or cucumber. Lastly, eight households were randomly chosen to be surveyed from each of the 50 selected villages. Three additional households were selected for each village as back-ups in case selected households could not be located or declined the interview.

Figure 3.2 Ward level sampling procedure

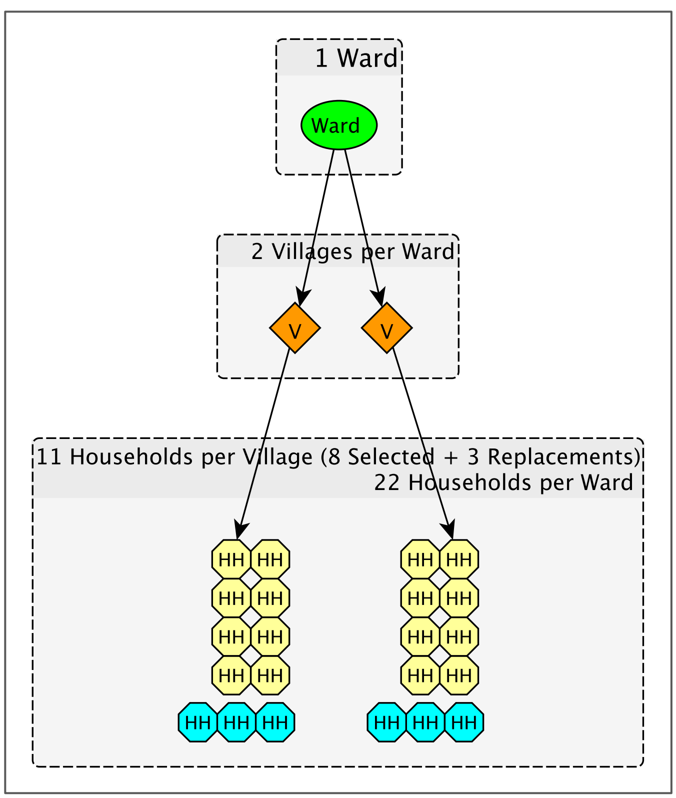


Figure 3.2 shows the sample selection procedure for each ward. A diagram for the entire sampling process can be found in the Appendix.

3.3.3 Data collection for Adoption Model

Because of the COVID-19 pandemic, the survey was delayed from its originally scheduled dates of May-June 2020 and instead was administered in March-April 2021. The survey team included eight enumerators and two supervisors. The enumerators were trained virtually on the questionnaire on March 7, 2021. As part of pre-survey training, a pre-test of 14 households was performed in Kanchanpur. Interviews were then conducted with 400 farm households, resulting in 397 usable questionnaires. Two observations were removed because they were duplicates, and one was removed because the survey was incomplete. Since our analysis focuses on determining the factors that affect IPM adoption by vegetable farmers, 51 observations were removed because the respondents had not grown vegetables in the past year. Of the remaining 346 vegetable farmers surveyed, 195 grew tomatoes, 263 grew cauliflowers, 183 grew onions, and 178 grew cucumbers.

As shown in Table 3.1*,* the majority (68%) of tomato farmers grew tomatoes in the winter season, and 14% and 23% of farmers grew tomatoes in the spring and summer seasons, respectively. Six percent of farmers grew tomatoes in two seasons. For cauliflower, most farmers (90.5%) produced in the winter season. A few farmers grew cauliflower in the spring (5%) and summer (5%) seasons, and a small number (3%) grew in two seasons. Onions are only grown in the winter season. For cucumber, the growing seasons are winter (23% of farmers), spring (36%), and summer (43%), with a small number of farmers producing in more than one season (2%).

Table 3.1 Vegetable production by season

Season	Tomato # of farmers (%)	Cauliflower # of farmers (%)	Onion # of farmers (%)	Cucumber # of farmers (%)
Winter	133 (68%)	238 (90%)	183 (100%)	41 (23%)
Spring	28 (14%)	14 (5%)	-	64 (36%)
Summer	45 (23%)	20 (8%)	-	76 (43%)
2+ Seasons	11 (6%)	9 (3%)	-	3 (2%)
Total	195	263	183	178

In addition to producing tomatoes in three different seasons, Nepali farmers produce tomatoes using two different farming methods. The first method of producing tomatoes is in an open field (possibly in a plastic tunnel). A plastic tunnel involves using polyethylene as a low-cost nonporous protective cover over open field plantings. Open field production is the primary method used by almost all (99%) tomato farmers. The other way to farm tomatoes is with a net house, an enclosed structure with agro-nets that allow sunlight moisture and air to pass through, which approximately 20% of farmers use. Most farmers using this method also farm tomatoes in an open field. Two tomato farmers from the survey only used a net house as their production method.

Table 3.2 2021 Survey tomato farming production methods

Tomato Production Methods			
	Open field or polyhouse:		
Net house:	No	Yes	Total
No	0	157	157
Yes	2	36	38
Total	2	193	195

3.4 Determination of Variables

3.4.1 Categorization of IPM Practices

To construct the adoption variable for this study, we looked at data on individual IPM practices. Because pest-management needs vary by vegetable, IPM packages include general vegetable IPM practices and crop-specific practices. For this survey, we used IPM packages from previous and current FTF programs to develop the list of IPM practices for each vegetable. Other than a few crop-specific practices (e.g., straw-mulching for onions), the IPM practices for cauliflower, onion, and cucumber were similar. The list of IPM practices for tomatoes was based on a package from a previous FTF survey performed in 2018 (Knaresboro, 2019). This allows us to compare the IPM adoption levels from this survey to the 2018 adoption levels.

Three of the four vegetables (tomato, cucumber, cauliflower) are grown in three seasons, and tomatoes are grown using two different production methods. To simplify data analysis, we grouped the pest management practices for each farmer across seasons and production methods. For example, if a farmer used the same IPM practice in two different growing seasons, we counted this as one use of that practice. This process enables the comparison of the adoption levels for IPM practices for vegetables grown in different seasons or using different production methods.

In analyzing the survey results, the complete list of IPM practices was divided into "simple" and "complex" practices. Simple practices are general farm practices (e.g., removing damaged plants) or practices that do not typically require additional skill or knowledge. Table 3.3 shows the IPM practices we categorized as simple and their respective adoption rates.

Table 3.3 Simple IPM practices by vegetable

Simple IPM Practices							
Tomato		**Cauliflower**		**Onion**		**Cucumber**	
Practice	*% Adopted*	*Practice*	*% Adopted*	*Practice*	*% Adopted*	*Practice*	*% Adopted*
Remove damaged plants	58.0%	Remove damaged plants	48.3%	Remove damaged plants	38.3%	Remove damaged plants	44.9%
Regular field inspections (OPEN)	48.7%	Sticky trap	19.0%	Straw mulching	23.0%	Sticky trap	25.3%
Destroy previous crop residue	42.1%	Disease-resistant variety	15.2%	Disease-resistant variety	9.8%	Disease-resistant variety	21.3%
Check seedlings before transplanting	18.5%	Intercrop	6.8%	Sticky trap	4.4%	Intercrop	10.1%
Do not grow other host crops and remove host weeds	16.9%	Select healthy seeds or sanitizing seed treatment	4.9%	Intercrop	3.3%	Raise seedlings using coco-pith	3.4%
Plastic mulch (OPEN)	11.4%	Grow seedlings in trays	3.0%	Select healthy bulbs or sanitizing treatment	2.2%	Bag fruits	2.2%
Check greenhouse net for holes (NET)	7.9%	Nursery net	1.1%	Grow seedlings in trays	1.1%		
Install a tight secure door (NET)	7.9%						
Grow seedlings in a netted nursery	3.1%						
Ensure pollination (NET)	2.6%						

For tomatoes, practices that are only used with the open-field production technique are labeled (OPEN). Similarly, the practices labeled (NET) are only used with a net-house production method. The adoption rate for these practices was calculated by taking the number of farmers using that practice divided by the total number of farmers using that production method.

We classified using biopesticides or pheromone traps as “complex” practices because they typically require additional knowledge or instructions to use. Farmers were asked if they used different biopesticides (e.g., neem products, *Trichoderma* spp., and *Bacillus thuringiensis* (Bt)) to control for plant diseases and pests. The various biopesticides were combined in the table below, and the adoption rate reflects the percentage of farmers who used at least one biopesticide.

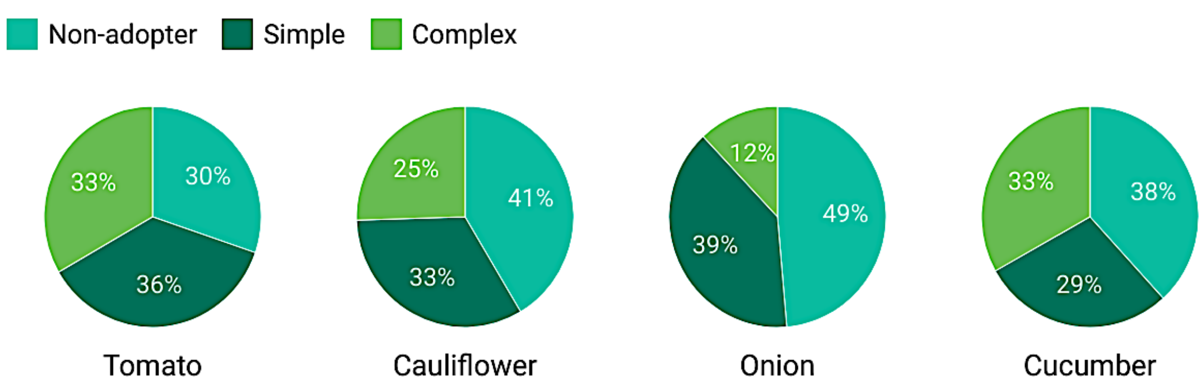
Table 3.4 Complex IPM practices by vegetable

Complex IPM Practices				
Practice	**Tomato** (% Adopted)	**Cauliflower** (% Adopted)	**Onion** (% Adopted)	**Cucumber** (% Adopted)
Pheromone traps	17.4%	13.7%	2.7%	21.3%
Biopesticides	30.4%	20.9%	10.4%	26.3%
Both	14.5%	9.1%	1.1%	14.5%
TOTAL	**33.3%**	**25.5%**	**12.0%**	**33.1%**

From Table 3.4, more farmers use biopesticides than pheromone traps. Approximately 14% of tomato and cucumber farmers use both biopesticides and pheromone traps. Comparatively, 9.1% of cauliflower farmers and a small amount (1.1%) of onion farmers use a biopesticide or pheromone trap.

Figure 3.3 shows the distribution of the three categories of adopters for each vegetable. "Simple adopters" are those that did not use complex practices but used at least one simple practice. "Complex adopters" are farmers that used at least one complex practice (pheromone trap or biopesticide) and may or may not have used simple practices. an economic regression. Farmers that did not use any IPM practices are classified as "non-adopters".

Figure 3.3 Adoption groups by vegetable



Tomato farmers are fairly equal in their distribution of adopters, with 33% complex adopters, 36% simple adopters, and 30% non-adopters. One out of four cauliflower farmers adopt complex practices. 33% of cauliflower farmers are simple-adopters, and a large portion (41%) of cauliflower farmers do not use any IPM practices. The majority of onion farmers are either simple adopters (39%) or non-adopters (41%), and only a small proportion of farmers (12%) adopt complex IPM practices. Lastly, one-third of cucumber farmers adopt complex practices, leaving 29% and 38% simple and non-adopters, respectively.

3.4.2 Determination of the Dependent Variable

For our analysis, there are numerous ways we can define adoption in a dependent variable. We needed a model that we could replicate across all four vegetables with the same definition of adoption so we can compare results. We defined complex adopters as those who adopted either a biopesticide or a pheromone trap because we wanted to examine the factors that influence a farmer to adopt any of the complex practices. Because of the minimal effort required to adopt simple practices, we grouped simple-adopters with non-adopters and used a binary variable to define adoption. In our model, a zero represents either a non-adopter or simple-adopter, and a one represents complex-adopters.

3.4.2 Explanatory Variable Selection for the Adoption Model

The explanatory variables in the model were selected by referencing relevant research to incorporate the most influential factors affecting farmers' adoption of IPM practices. The purpose and the predicted sign of each variable is presented below.

1. Age

The age of the primary decision-maker in the household is a continuous explanatory variable in the adoption model, represented by *age*. The literature regarding the effect of age on technology adoption has produced inconsistent results. Some studies found that older farmers were more risk-averse and, therefore, unwilling to try new technologies (Mauceri et al., 2007). On the other hand, older farmers may have more experience, which enhances their decision-making ability. Because of these mixed results, we predict age to have an ambiguous relationship with the adoption of complex practices.

2. Female

The gender of the primary decision-maker, *female*, is a binary explanatory variable in the adoption model. A binary, or dummy, is used to quantify categorical variables in regression analysis. A one indicates that the primary decision-maker is female, and zero represents a male respondent or two people interviewed together. In general, adoption studies have produced mixed results on how gender affects adoption (Mishra et al., 2020). Using a dynamic adoption model, Mishra et al. (2020) found that female-headed households have fewer learning opportunities, and since self-learning is a significant determinant in technology adoption, this causes a greater disparity between adoption rates of male- and female-headed households. Another study found that while farmers living in a female-headed household were less likely to adopt a new agricultural technology, the gender of the farmer did not affect the adoption decision (Doss & Morris, 2000). In Nepal, women have less access to finance and market facilities, land ownership, and bargaining power (FAO, 2019). In addition, most extension agents are men, and this lack of female representation in agricultural professions makes female farmers less likely to seek extension services compared to male farmers (FAO, 2019). Unfortunately, our questionnaire did not ask farmers about the gender of their extension agents, so we are not able to control for this in the model. Because IPM knowledge and access to inputs are important factors in adoption decisions, female primary-decision makers, with less access to these resources, may be less likely to adopt IPM practices. Therefore, we suspect that there could be a negative relationship between *female* primary decision makers and complex IPM adoption.

3. Experience in vegetable farming

In each vegetable's model, the primary decision maker's experience (in years) farming that specific vegetable (tomato, cauliflower, onion, or cucumber) is represented by a continuous regressor, *exp*. Farmers with more experience have had more time to increase their knowledge and is a form of informal education. Increasing experience can increase a farmer's ability to judge the profitability of a new technology. Because of this, we expect *exp* to have a positive correlation with adoption of complex IPM practices.

4. Education

Education involves a formal training process in which individuals acquire higher-level thinking skills that give them a better understanding and awareness of IPM practices (Tolchinsky, 1989). In the survey, the respondents were asked to identify their highest education level: none, primary, secondary, SLC completion, or college. In Nepal, SLC, or School Leaving Certificate, is a higher-secondary exam taken by 11^{th} and 12^{th}-grade students and "determines (the) educational career path of him/her" (Office of the Controller of Examinations (OCE), 2019). The level of education obtained by the primary decision-maker is a categorical variable with four levels represented as four indicator variables (*none, primary, secondary,* and *collegeslc)* in the adoption model. Because only a few farmers had college-level (undergraduate or graduate) education, we combined college education with completion of the SLC exam. The combined variable, *collegeslc*, represents if primary decision-makers have received college education or completed the SLC exam. The dummy variable *none* is left out as the reference group. We expect that as the level of education increases, so will the adoption of complex practices.

5. Farm size

Farm size is commonly regarded as a proxy variable for wealth or level of living. Land is a source of credit, so larger farms are more likely to afford the fixed costs that come with adopting a new technology. Small scale farmers are typically more risk-averse and subject to credit constraints that limit their ability to adopt a new technology (Feder, 1979). Therefore, we expect farm size to have a positive effect on IPM adoption. In the IPM adoption model, the primary decision-maker's farm size is a continuous variable represented by *land,* measured in ropani. Ropani is a commonly used unit for land area in Nepal; one hectare is equal to 19.66 ropani (GON Ministry of Agricultural Development & Agri-Business Promotion and Statistics Division, 2016).

6. Migrant in the household

In Nepal, one in four households reported they have a household member that is absent or living out of the country (GON Central Bureau of Statistics (CBS), 2012). The presence of a migrant in the household of the primary decision-maker is a binary explanatory variable represented by *migrant* in the model. We considered a household member who spends more than three months away from the household a year to be a migrant. We think there could be a negative relationship between the presence of a migrant and adoption because the more time farmers spend away from their farms, the less likely they are to commit to adopting a new technology, especially if it requires additional labor to implement it.

7. Household labor

The number of farmworkers in the primary decision maker's household is a continuous variable represented by *labor* in the model. Pest management practices can be labor intensive and having more household members who work on the farm can help to meet this demand. Because of this, we expect *labor* to have a positive relationship with adoption.

8. Distance to an agricultural extension office

A household's distance to the nearest agricultural extension office (in kilometers) is a continuous independent variable in the adoption model, represented by *dexten*. An agricultural extension office serves to increase farmer awareness on currently available technology. Studies have shown that farmer is more likely to participate in extension services if an office is within close proximity to their farmland (Adhikari & Nepal, 2016). Therefore, *dexten* is expected to have a negative effect on IPM adoption.

9. Distance to agro-vet

A household's distance to the nearest agro-vet (in kilometers) is represented by the continuous independent variable, *dvet*. In Nepal, an agro-vet provides farmers with chemical pesticides and non-synthetic, or IPM, pest-management supplies. IPM products that an agro-vet can provide include pheromone traps, light traps, bio-pesticides, and microbial pesticides. Because an agro-vet can supply both IPM and non-IPM products, we expect that *dvet* will have an ambiguous relationship with adoption of complex IPM practices.

10. Community Business Facilitator

Advice from a Community Business Facilitator (CBF) is represented by the binary variable, *cbf*, in the model. In a village, a community business facilitator serves to provide farmers a way to access agricultural inputs, which in turn helps ease a possible constraint in pest management adoption. We expect *cbf* to have a positive relationship with adoption of complex pest control practices.

11. Organization membership

The primary decision maker's involvement in a community organization is the binary explanatory variable, *memb*, in the model. A one represents membership in an organization. A zero indicates that the primary decision maker is not a member of an organization. Membership in a community organization can be particularly impactful for small-scale farmers in developing countries to gain access to resources such as training, inputs, markets, credit, and general information. Agricultural marketing groups or rural credit cooperatives are examples of community organizations a farmer can choose to be involved in. Since we expect that farmers who participate in group activities are more likely to have better access to information, we predict that membership in an organization will positively affect IPM adoption.

12. IPM training

Attending training on integrated pest management practices is represented by the discrete variable, *train,* in the model. IPM training increases farmers' awareness of these practices, and we expect that farmers who are more aware of IPM's costs and benefits will be more likely to adopt. Therefore, we expect training to have a positive relationship with adoption of complex IPM practices. Since we suspect training attendance may be correlated with unobservable error terms, we correct this endogeneity problem with an instrumental variable approach that will be further discussed later.

13. Severity of pests

Respondents were asked to measure (on a scale of zero to three) the severity of all pest problems (insects, diseases, viruses, and rodents) on their farm in the past year. The severity of pests is measured in terms of damage to crops and damage to yield. A zero indicated no damage to either crop or yield. A one represented low severity, some damage to crops, but the yield was unaffected. Two characterized medium severity, some damage to both crops and yield. Lastly, a three represented high pest incidence, significant damage to crops and yield. Total pest severity is represented in the model by the dummy variable: *severe*. In our model, a one for severity indicates medium or high pest severity. A zero indicates low or no pest severity. We assume that as pests' damage to crops and yield increases, farmers will turn to various methods of pest control including chemical pesticides or integrated pest management. When a farmer chooses to use a control method, pest severity decreases, thus decreasing the need for pest management products. Therefore, we expect *severe* to have an ambiguous with IPM adoption.

14. District

The survey took place in four different districts located in the Terai and Hill regions: Kanchanpur (Terai), Kavrepalanchok (Hills), Surkhet (Hills), and Banke (Terai). To control for the differing agro-climatic conditions in these districts, a categorical variable with four levels (represented as four indicator variables) is included in the model: *district1* for Surkhet, *district2* for Banke, *district3* for Kanchanpur, and *district4* for Kavrepalanchok. Surkhet, *district1*, serves as the base level and is omitted from the regression. A one indicates that the primary decision maker's farm is located in that district. Since it is hard to predict how each district's climate affects a farmer's decision to adopt IPM practices, we expect the district variables to have ambiguous relationships with IPM adoption.

15. Input availability during COVID-19 Pandemic

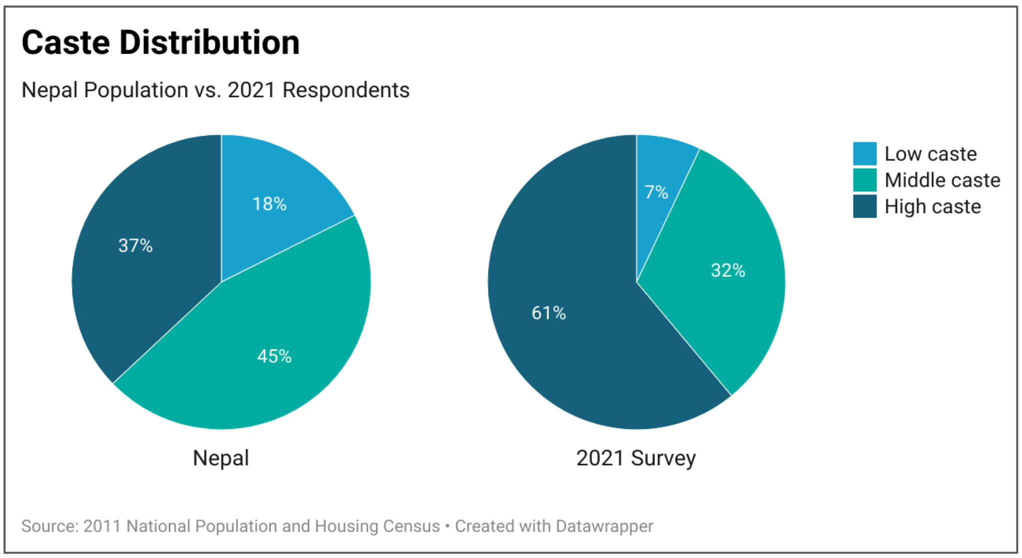
During the COVID-19 pandemic and lockdown, many Nepalese farmers could not access input supplies for their farms. We account for this by including the binary variable, *input,* in our model. In the questionnaire, we asked farmers if they have been able to obtain inputs (seed, fertilizers, pest management products) for their farms during the COVID-19 pandemic. Based on this information, a zero for *input* indicates that the farmers have not been able to obtain inputs, and a one indicates the farmers have had access to inputs during the COVID-19 pandemic. Since farmers will not adopt technologies if their inputs are not easily accessible, we expect this variable to have positive relationship with adoption (Feder et al., 1985).

16. Caste/ethnic group

A Nepali farmer's caste or ethnic group affects their economic and social capital. The 2011 Nepal Population and Housing Census found that lower caste groups (Dalit and other Terai/Madhesi) have lower school attendance, less access to mobile phones, and lower literacy rates (GON Central Bureau of Statistics (CBS), 2014), which can affect a household's decision to adopt complex IPM practices. A 2018 study on factors affecting the adoption of climate-smart agricultural (CSA) practices in India found that households belonging to a “general” caste were more likely to adopt CSA practices compared to households from lower and “scheduled” caste groups (Aryal et al., 2018). In this research survey, respondents identified as one of the six categories of caste/ethnic groups: Brahmin/Chhetri, Newar, Dalit, Janajati, Muslim, Other Terai/Madhesi groups, and Other. The majority (57%) of the survey respondents belonged to the Brahmin/Chhetri caste group while some of the caste groups (Muslim and Newar) make up less than 5% of the respondents. To address the issue of limited respondents from some caste groups, we consolidated the six groups into three categories (high, middle, and low) based on that group’s economic access and historical position in society.

The high caste group consists of Brahmin/Chhetri, Newar, and Other. The "Other" category in the high caste group included four observations belonging to the "Thakuri” caste/ethnic group. Several studies have identified Thakuri’s as part of the Hill Chhetri group; we replicated this grouping and included Thakrui in the high-caste group (Bennett et al., 2008; The World Bank & DFID Nepal, 2006). The middle group consists of Janajati, Other Terai/Madhesi, and Other (noncategorized). Lastly, Dalits and Muslims are in the low group because they are considered the most marginalized in Nepali society. A categorical variable with three caste levels was created and represented as three indicator variables in the model. The three indicator variables are *highcaste*, *midcaste*, and *lowcaste*, representing the high-caste group, middle-caste group, and low-caste group respectively. The high caste group, *highcaste*, is left out of the model and serves as the base level. Since a household's caste affects their ability to access important farming resources, we expect that the higher caste groups (Brahmin/Chhetri and Newar) will be more likely to adopt complex practices.

Figure 3.4 Caste distribution from 2011 Census vs. 2021 Survey



An important note is the caste/ethnic group representation in the survey compared to the national average. The figure above shows the caste distribution from the 2021 survey compared to Nepal's caste distribution (from the 2011 Census). According to the 2011 Census, 37% of Nepal's population is high-caste, 45% is middle-caste, and 18% are in the marginalized caste/ethnic group. In our research, most of the surveyed vegetable farmers (61%) are high-caste, 32% are middle-caste, and only 7% are low-caste. This difference in caste distribution could indicate two things: 1) our survey is not an accurate representation of Nepali vegetable farmers due to sampling errors, or 2) a smaller portion of middle- and low-caste members are vegetable farmers. Since research has shown that marginalized groups are less likely to own or rent land, and therefore have less ability to farm, we suspect 2) is more likely. Likewise, a 2011 survey on land tenure in Nepal found that 46% of Tarai Dalits and 31% of Hill Dalits were not involved in farming (Dhakal, 2011).

A summary table of the explanatory variables used in the model is shown in Table 3.5.

Table 3.5 Explanatory variable selection for adoption model

Explanatory Variable	Description	Type	Description of Values	Predicted Sign
age	Age in years	Continuous	Years	Either
labor	# of agricultural workers in the household	Continuous	# of workers	+
migrant	Presence of a migrant in the household	Discrete	0 = No, 1 = Yes	-
dvet	Distance from the farm-household to an agro-vet in kilometers	Continuous	Kilometers	Either
dexten	Distance from the farm-household to an agricultural extension office in kilometers	Continuous	Kilometers	-
exp	Years of experience the primary decision maker has in tomato, cauliflower, onion, or cucumber farming	Continuous	Years	+
land	Amount of land the household farms	Continuous	Ropani	+
memb	If the primary decision maker is a member of a farm or community organizations	Discrete	0 = No, 1 = Yes	+
primary	If primary education is the highest level of schooling the primary decision maker has received	Discrete	0 = No, 1 = Yes	+
secondary	If secondary education is the highest level of schooling the primary decision has received	Discrete	0 = No, 1 = Yes	+
collegeslc	If SLC completion or college is the highest level of schooling the primary decision maker has received	Discrete	0 = No, 1 = Yes	+
severe	If the farm household experienced severe pest damage	Discrete	0 = No/Low damage 1 = Medium/High damage	Either
cbf	If the primary decision maker received advice from a Community Business Facilitator	Discrete	0 = No, 1 = Yes	+
input	If the farm-household has had access to inputs during COVID	Discrete	0 = No, 1 = Yes	+
female	If the primary decision maker is female	Discrete	0 = No, 1 = Yes	
district2	If the farm is located in Banke	Discrete	0 = No, 1 = Yes	Either
district3	If the farm is located in Kanchanpur	Discrete	0 = No, 1 = Yes	Either
district4	If the farm is located in Kavre	Discrete	0 = No, 1 = Yes	Either
midcaste	If the primary decision maker is from a middle-caste/ethnic group	Discrete	0 = No, 1 = Yes	-
lowcaste	If the primary decision maker is from a marginalized caste/ethnic group	Discrete	0 = No, 1 = Yes	-

train	If the primary decision maker has received IPM training	Discrete	0 = No, 1 = Yes	+

none, district4, and *highcaste* are base variables that are omitted from the model

3.4 Econometric Model for Predicting Adoption

3.4.1 Functional form

A typical model of farmers' choice to adopt IPM is as follows:

IPM adoption = f (age, education, land tenure, income, distance to market, member of farm organization, IPM training)

In this study, we used a binary variable for adoption, represented by *adopt.* A binary variable is a limited dependent variable or a dependent variable with a restricted range of values (Wooldridge, 2013). Limited dependent variables (LDV) are most often used in models with cross-sectional data. Binary response models take the form

$$(1)\ P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) = G(\beta_0 + x\beta),$$

where $G\ (z) = z$ is the identify function taking on values between zero and one for all real numbers z (Wooldridge, 2013). When looking at the adoption of a group or combination of practices (represented as a discrete dependent variable), a nonlinear model is typically used (Norton & Swinton, 2009). Compared to a non-linear model, a linear probability model (LPM) can give out-of-bound predictions that are less than zero and greater than one. Therefore, we chose a non-linear model that uses maximum likelihood estimation (MLE) instead of a linear model that uses ordinary least squares (OLS).

Logit and probit models are the two most common non-linear functions. In logit models, G is the cumulative distribution function for a standard logistic random variable. In the probit model, G is the standard normal cumulative distribution function (cdf) (Wooldridge, 2013). Both models can be derived from an underlying latent variable model represented as

$$(2) \quad y^* = \beta_0 + x\beta + e, \qquad y = 1[y^* > 0],$$

where y* is an unobserved, or latent, variable and 1[·] is the indicator function that defines a binary outcome (Wooldridge, 2013). The indicator function only takes on the value of one if the events in the bracket are true, the alternative being zero (Wooldridge, 2013). The error term, in equation 2, e, is symmetrically distributed around zero for both probit and logit models (Wooldridge, 2013). For this study, the **probit model** was chosen because of its normality assumption and is expressed as the integral

$$(3) \quad G(z) = \Phi(z) = \int_{-\infty}^{z} \phi\,(v)dv,$$

and $\phi(z)$ is the standard normal density represented as

$$(4) \quad \phi(z) = (2\pi)^{-1/2} \exp\left(-\frac{z^2}{2}\right).$$

G is an increasing function that only takes on values between zero and one for all values of the parameters and the x_j (Wooldridge, 2013). To estimate the magnitude of the effects of the explanatory variables, x_j, on the binary response probability $P(y = 1|x)$, we take the partial derivative for a continuous variable

$$(5) \quad \frac{\partial p(x)}{\partial x_j} = g(\beta_0 + x\beta)\beta_j, \quad where\ g(z) = \frac{dG}{dz}(z),$$

where g is the probability density function (Wooldridge, 2013). A modified version of the partial effects for a binary explanatory variable, x_1, is calculated by:

$$(6) \quad G(\beta_0 + \beta_1 + \beta_2 x_2 + \cdots + \beta_k x_k) - G(\beta_0 + \beta_2 x_2 + \cdots + \beta_k x_k)$$

(Wooldridge, 2013).

3.4.2 Structural equation of the adoption model

The structural form of the binary response model is

$$
\begin{aligned}
P(adopt = 1 \mid x) \\
&= G(\beta_0 + \beta_1\, age + \beta_2 labor + \beta_3 migrant + \beta_4 dvet + \beta_5 dexten \\
&+ \beta_6 exp + \beta_7 land + \beta_8 memb \\
&+ \beta_9 primary + \beta_{10} secondary + \beta_{11} collegeslc + \beta_{12} severe \\
&+ \beta_{13} cbf + \beta_{14} input + \beta_{15} female + \beta_{16} district2 + \beta_{17} district3 \\
&+ \beta_{18} district4 + \beta_{19} midcaste + \beta_{20} lowcaste + \beta_{21} train + \mu)
\end{aligned}
$$

where *adopt* is a binary dependent variable representing either one, a complex adopter, or zero, a non-complex adopter. G is a function with values between zero and one for all real numbers z (Wooldridge, 2013). x represents the full set of explanatory variables, β_0 is the constant, μ is the error term, and $\beta_1 - \beta_{20}$ are the coefficients for the explanatory variables $age, labor, migrant, dvet, dexten, exp, land, memb, primary, secondary, collegeslc,$ $severe, cbf, input, district2, district3, district4, midcaste, lowcaste,$ and $train$.

3.4.3 Endogeneity in the model

When a variable, x, is correlated with the error term, u, it is called an endogenous explanatory variable and if that correlation is not accounted for it can lead to biased results (Wooldridge, 2013). In the adoption model, we suspected that *train*, which represents whether a primary decision maker has received IPM training, might be correlated with the error term. Farmers may voluntarily choose to participate in IPM training based on unobservable characteristics such as innovativeness that cannot be controlled for in adoption the model (Ricker-Gilbert et al., 2008). In addition, we do not know whether or not the selection of villages in which training takes place is random.

To deal with this, an instrumental variable can be used to obtain the coefficient of the endogenous variable, x. (Wooldridge, 2013). A good instrument satisfies two assumptions. The first assumption (equation 8) is instrument exogeneity, or z is uncorrelated with u.

$$(8)\ \ Cov(z, u) = 0$$

The second assumption (equation 9) of a good instrument is that z is correlated with x, or otherwise known as instrument relevance (Wooldridge, 2013).

$$(9)\ \ Cov(z, x) \neq 0$$

To determine if an instrument is suitable, these assumptions should be tested in some manner. To test if the instrument, z, is correlated with the endogenous variable, x, Wooldridge (2013) suggests estimating a regression between x and z,

$$(10)\ \ \ x = \pi_0 + \pi_1 z + v$$

and the instrument relevance holds if $\pi_1 \neq 0$

Since we suspected IPM training to be endogenous, we took this into account by regressing *train* on all explanatory variables included in the adoption model and plus one instrumental variable, *villtrain*. The continuous variable, *villtrain,* represents the proportion of people in the primary decision maker's village that are trained in IPM. This controls for the fact that not all villages have access to training programs, and farmers will not have the option to participate. This instrument was chosen because it is likely to affect participation in IPM training and affects IPM adoption only through participation in IPM training. In addition, this instrument has been used in other adoption studies and shown to be a valid instrument (Knaresboro, 2019; Vaiknoras, 2019). Lastly, the instrumental variable was estimated using the maximum likelihood estimation (MLE) method.

To check for endogeneity, we examined the correlation between the residuals in the IPM training regression and the adoption regression. For tomato, onion, and cucumber, the correlation coefficient was statistically insignificant (at a 5% level), meaning that we fail to reject the null hypothesis that IPM training is exogenous. Since IPM training was found to be exogenous in the tomato, onion, and cucumber models, we did not use the IV approach to estimate the determinants of IPM adoption.

For cauliflower, the correlation coefficient was statistically significant at a 5% level, so we reject the null hypothesis that IPM training is exogenous. Therefore, receiving IPM training is endogenous in the cauliflower adoption model and the unobservable factors that increase the chance of being trained in IPM affect the chance of adopting complex IPM practices. Because of this, we determined it was necessary to use the instrumental variable approach when estimating the cauliflower adoption model. Summary statistics for each explanatory variable discussed (including base groups) are shown in Table 3.6.

Table 3.6 Summary statistics for all variables by crop

Variable	Description	**Tomato** mean or % (variable = 1)	**Cauliflower** mean or % (variable = 1)	**Onion** mean or % (variable = 1)	**Cucumber** mean or % (variable = 1)
age	Age in years	41	39	40	41
labor	# of agricultural workers in the household	3.17	3.00	3.24	3.22
migrant	% of households with migrants	29%	25%	33%	25%
dvet	Distance to agro-vet in kilometers	3.58	3.53	3.71	3.36
dexten	Distance to agricultural extension office in kilometers	4.83	4.76	4.89	4.50
exp	Years of crop experience	12.95	11.86	13.38	12.94
land	Land farmed in Ropani	12.09	11.29	11.99	11.46
memb	% of farmers that are members of a farm or community organizations	84%	82%	81%	84%
none	% of farmers with no education	25%	21%	28%	25%
primary	% of farmers with primary education	29%	27%	26%	26%
secondary	% of farmers with secondary education	21%	27%	22%	24%
collegeslc	% of farmers with SLC completion or college education	25%	25%	23%	25%
severe	% of farmers that experienced severe pest damage	41%	32%	23%	37%
cbf	% of farmers that received advice from a Community Business Facilitator	20%	20%	14%	20%
input	% of farmers that had access to inputs during COVID	53%	53%	52%	54%
female	% of farmers that are female	59%	63%	68%	57%
district1	% of farmers from Surkhet	25%	23%	28%	22%
district2	% of farmers from Banke	34%	32%	34%	22%
district3	% of farmers from Kanchanpur	24%	24%	25%	28%
district4	% of farmers from Kavre	16%	22%	13%	28%
highcaste	% of farmers from a high-caste/ethnic group	58%	59%	60%	61%
midcaste	% of farmers from a middle-caste/ethnic group	35%	35%	33%	32%
lowcaste	% of farmers from a marginalized caste/ethnic group	6%	7%	7%	7%
villtrain	Proportion of people in farmer's village that was trained in IPM	0.49	0.49	0.47	0.47
train	% of farmers with IPM training	53%	52%	45%	50%
Number of observations		195	263	183	178

Chapter 4. Economic Impact Analysis

4.1 Literature Review

We reviewed relevant literature to develop a framework to measure the economic impacts of IPM practices. As discussed in the previous chapter, farmers will adopt a technology when there is sufficient evidence of its profitability. Researchers use economic impact assessments to assess a technology's benefits (environmental, consumer, producer, health, and well-being) at the farm, field, or market level (Norton, Alwang, Kassie, et al., 2019). Impact assessments can also be used by programs wishing to link IPM activities to impact.

Most economic impact assessments look at the effect of a single technology or specific crop/pest combination (Kassie et al., 2018; Norton, Alwang, Kassie, et al., 2019). For example, Myrick et al. (2014) found that biocontrol programs are an advantageous method of control for the devastating papaya mealybug in India, resulting in increased production and incomes and Rakshit et al. (2011) estimated significant economic benefits ($3 to $6 million) from using pheromone traps to manage fruit fly infestation on sweet gourd in Bangladesh.

Because synthetic pesticides can have significant impacts on health and the environment, using alternative methods of control such as IPM has important environmental benefits. (Norton & Swinton, 2009). Since few environmental benefits are valued in the market, some researchers instead look at how adopting IPM practices affects synthetic pesticide use and expenditures (Rahman et al., 2018; Sanglestsawai et al., 2015). Rahman et al. (2018) found that farmers who adopted IPM practices reduced their synthetic pesticide applications and saved, on average, $25 in Bangladesh. Similarly, Sanglestsawai et al. (2015) determined that farmers who attended IPM training (through farmer field schools) reduced their insecticide use and expenditures in the Phillippines. Another way to value IPM's environmental benefits is a contingent evaluation or willingness-to-pay study (Cuyno et al., 2001). Using this method, Cuyno et al. (2001) estimated that an onion IPM program led to annual environmental benefits of \$150,000 for six villages in the Philippines.

Recently, work has been done to disaggregate economic benefits to population subgroups (Moyo et al., 2007; Zeng et al., 2015). Moyo et al. (2007) employed this strategy in Uganda to estimate the effects of a new peanut variety on poverty using poverty indices. Similarly, Zeng et al. (2015) estimated that improved maize varieties decreased the poverty headcount ratio in Ethiopia by 0.8-1.3% in a single year.

The benefits from technology adoption can vary widely by geographic area due to differences in climate (e.g., elevation, rainfall, temperature) and commodity-market structure (Mills, 1997). Even though regions differ in the crop's production base, consumption, and adoption rate, most studies aggregate benefits to a whole country rather than separate analyses by geographic regions.

This study aims to build evidence on the cost and benefits of using IPM practices by looking at the economic impacts of IPM in two different growing regions (the Hills and the Terai) in Nepal.

4.2 Theoretical framework

Adoption of an innovative technology by many individuals can lower per-unit production costs and increase productivity, shifting a commodity's supply function outward (Alston et al., 1995; Norton & Swinton, 2009). To demonstrate this, the initial supply curve is defined as

$$(1) \qquad Q_{sj} = \alpha + \beta P_j$$

where Q_{sj} is the initial supply of commodity j, α is the intercept, β is the slope, and P_j is the price of the commodity. A unit-cost reduction in price from a technology-induced change in supply is

$$(2) \qquad Q_{sj} = \alpha + \beta\left(P_j + k\right) = (\alpha + \beta k) + \beta P_j$$

where k is the supply shift (Alston et al., 1995). As we mentioned, the technology-induced supply shift for an individual farmer involves two components: 1) productivity changes that occur if inputs are held at the pre-technological change optimum values, and 2) the changes to optimal input combinations under the new technology (Alston et al., 1995). There are two main approaches to estimate the effects of a supply curve shift: 1) econometric, and 2) index-number. A parametric, or econometric, approach involves estimating a production function, cost function, or profit function (Alston et al., 1995). An index-number approach uses aggregating methods to measure the source of growth in agricultural output or productivity. One advantage of an index procedure is that it produces consistent input and output aggregates that can be used for describing production-related data and estimating aggregate production, profit, and cost functions (Alston et al., 1995). An economic surplus method uses indexing measures to calculate the aggregate benefits from a technology-driven supply shift. We use an economic surplus approach as part of the second objective of this study, to evaluate the financial and economic performance of IPM practices.

4.3 The Basic Economic Surplus Model

The economic surplus approach has long been used to calculate the economic returns of an agricultural technology or research program (Griliches, 1958; Peterson, 1967). Peterson (1967) used the economic surplus approach to measure the benefits of poultry research, and Griliches (1958) used the surplus approach to calculate the net social returns from hybrid corn research. The concept of economic surplus includes the surpluses or benefits that accrue to consumers as well as producers (Currie et al., 1971). The benefits to consumers are called "consumer surplus," which is the value of extra utility that a consumer gets from buying the commodity at that particular price (Currie et al., 1971; Marshall, 1920). “Producer surplus” is the benefits a producer gets by selling their product at the market price level over and above what they would make if they produced nothing (Nicholson & Snyder, 2012). The sum of consumer surplus and producer surplus equals total surplus.

The steps in an economic surplus analysis are: 1) calculating the supply-shift (or K-factor), 2) gathering information on the extent of the technology's adoption and estimating rates over time, and 3) using 1) and 2) as well as market-related data (quantity, prices, elasticities, discount rate, exogenous growth of supply and demand) to estimate the technology's total costs and benefits, net present value, and internal rate of return on the investment (Alston et al., 1995; Moyo et al., 2007; Mutangadura, 1997).

Several assumptions are critical to this research analysis. The first assumption is that the supply-and-demand curves have linear functional forms (Alston et al., 1995). Also, in this study we assume the technology-induced supply shift is parallel. Two additional assumptions are that the model is static (i.e., independent of time) and competitive market clearing is imposed, which means that the model is in perfect equilibrium where the quantity supplied equals the quantity demanded (Alston et al., 1995). The last assumption is that Harberger’s conventional framework for applied welfare analysis is enforced. In his framework, Harberger defines three postulates, which are:

1. For a given unit, the competitive demand price is equal to the value to the individual demander.

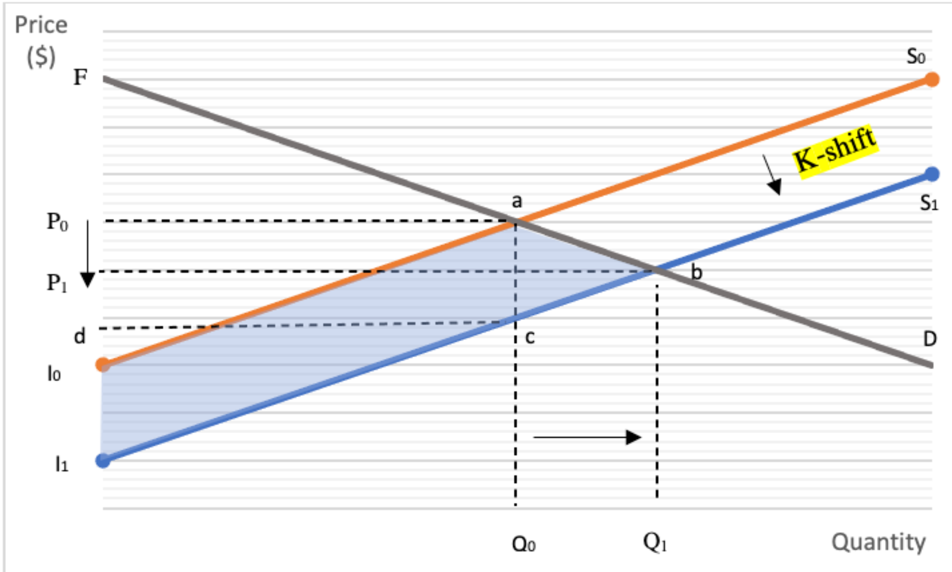
2. For a given unit, the competitive supply price measures the value of that unit to the individual supplier.
3. Lastly, when looking at the net impacts of a technology on total welfare, the costs and benefits that accrue to each member of the relevant group, should be added without regard to the individual(s) to whom they accrue (Harberger, 1971).

Using these assumptions, the benefits from a technological-induced supply shift can be estimated.

One of the major criticisms of the economic surplus approach involves Harberger's third postulate and its assumption of equal weights of welfare gains to all individuals in the relevant group. Some researchers argue that a technological change may impact the welfare of farming households differently, and studies should account for initial wealth endowments to accurately estimate the benefits of a technology (Moyo, 2004). Another criticism of the surplus method is that since it holds income constant, other measures such as equivalent variation or compensating variation may better capture the welfare effects from a price change (Moyo, 2004). Lastly, since producer surplus only accounts for variable costs, it ignores how fixed costs can affect profit (Moyo, 2004). Since our study does not handle distributional issues and focuses on changing variable costs, these criticisms are not concerning, and it is acceptable to use the economic surplus method.

A simple closed economy model is shown in Figure 4.1 where S_0 is the initial supply curve and S_1 is the new supply curve, which results from a new technology.

Figure 4.1 Closed economy model



When the supply curve shifts from S_0 to S_1, the equilibrium shifts from a to b. The equilibrium price and quantity shift from Q_0 and P_0 to Q_1 and P_1. The supply or K-shift relative to the initial price is equal to $\frac{P_0 - d}{P_0}$. The resulting benefit is equal to the area between the two supply curves, S_0 and S_1, and below the demand curve, D (Alston et al., 1995). This area is the change in total surplus ($\Delta TS = area\ I_0abI_1$), which comes from a) the cost savings on the original quantity (area I_0acI_1) and b) the increased production and consumption ($area\ abc$) (Alston et al., 1995). The triangle abc is estimated by subtracting the increase in production costs ($area\ Q_0cbQ_1$) from the increase in consumption (area Q_0abQ_1) (Alston et al., 1995).

Total benefits ($area\ I_0abI_1$), can be divided into the benefits to consumers and the benefits to producers. The total benefit to consumers is equal to the change in consumer surplus ($\Delta CS = area\ P_0abP_1$). Consumer surplus is the difference between what a consumer pays and what they are willing to pay (Marshall, 1920). Therefore, when the supply curve shifts from S_0 to S_1, consumer welfare increases because consumers can buy goods at a lower price (Alston et al., 1995).

Producer surplus is the area between the market price level and the supply curve. The change in producer surplus is calculated by subtracting $area\ P_0aI_0$ from $area\ P_1bI_1$. Because of the initial assumptions (parallel supply-shift), the change in producer surplus is equal to the area P_1bcd. The size of this change in producer surplus depends on the elasticities of supply and demand and the relative change in the producer's supply curve. While producers can sell more goods at this lower price, their costs and revenues are affected (Alston et al., 1995). For goods with inelastic demand, this increase in production decreases revenue (Alston et al., 1995). Ultimately, producers will benefit if the supply shift causes the total cost to decrease and revenue to increase (Alston et al., 1995).

4.4 Model Specification

4.4.1 Time Period and Location

In response to the overuse of synthetic pesticides on vegetable crops and the success of IPM elsewhere, the USAID-funded IPM Innovation Lab (IPM-IL), along with local implementing partners and government agencies, began to develop and test individual IPM components in 2006. While testing of full-season vegetable IPM packages began in 2010, additional limited testing to refine IPM packages took place in 2015-2016. Therefore, our model will start in 2015, and we will project benefits out to 2026. We obtained information on the yield and cost changes that result from IPM technologies using partial budgets from field trials performed by iDE in 2019. Because the trials took place in two different districts, Banke and Surkhet, we applied the surplus approach to estimate IPM benefits for these two regions. We calculated the economic benefits of using IPM practices for three vegetables (tomato, cauliflower, and onion) in Banke and four vegetables (tomato, cauliflower, onion, cucumber) in

Surkhet. Field trials were not conducted for cucumbers in Banke so we could not perform an impact assessment.

4.4.2 Open vs. Closed Economy

An economic surplus approach can be adjusted based on the type of economy being studied. A closed-economy model assumes there is little international trade in the economy for that product and both consumers and producers are beneficiaries of IPM practices as demonstrated by the basic surplus model shown before as Figure 4.1. In an open economy model, vegetable producers are the primary beneficiaries of IPM adoption through increased sales or household consumption (Moyo et al., 2007). To determine the most appropriate model, we analyzed Nepal's trade in vegetables.

To decide if Nepal qualifies as a small open economy, we looked at vegetable exports and imports relative to total domestic vegetable production and world trade in 2015. As shown in Table 4.1, Nepal is heavily reliant on onion imports, with supply almost one-third of total consumption (GON Ministry of Agricultural Development & Agri-Business Promotion and Statistics Division, 2016). In addition, the value of Nepal's onion imports amounts to 0.55% of total world onion imports (UNSD & DESA, 2021). Comparatively, Nepal's tomato, cauliflower, and cucumber imports make up less than .02% of total world imports (UNSD & DESA, 2021). Nepal's tomato, cauliflower, onion, and cucumber exports are a minor share (less than 0.03%) of total world vegetable exports (UNSD & DESA, 2021).

Table 4.1 Nepal's trade in tomato, cauliflower, onion, and cucumber in 2015

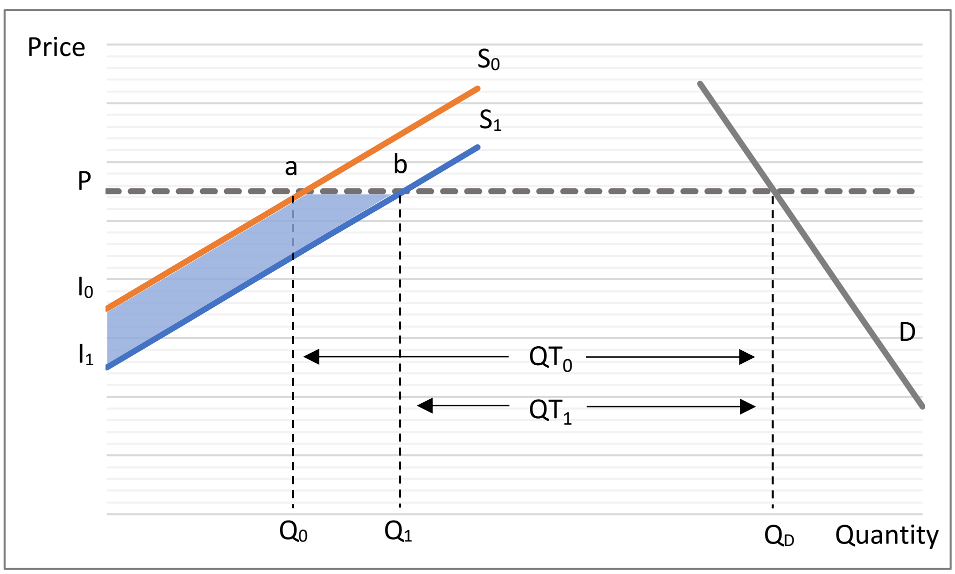
2015-2016	Imports (Metric Ton)	Exports (Metric Ton)	Total Production (Metric Ton)	Consumption (Metric Ton)	% Imported out of Total Consumption

Tomato	12,345	538	386,825	398,631	3.1%
Cauliflower	244	1,481	550,045	548,808	0.04%
Onion	97,391	35	238,591	335,946	29%
Cucumber	22	1.5	159,042	159,062	0.01%

(GON Ministry of Agricultural Development & Agri-Business Promotion and Statistics Division, 2016).

Since Nepal does not have a dominant presence in the global tomato, cauliflower, or cucumber markets and does not rely on imports, a closed economy model (as shown in Figure 4.1) is suitable. Because Nepal depends on imports for a significant portion of onion consumption but is only a small importer in the global onion market, Nepal is classified as a small open economy for the onion surplus analysis. The economic surplus model for a small open economy is shown in Figure 4.2.

Figure 4.2 Small importing country model



In a small open economy model, the initial equilibrium is Q_D, Q_0, and P, representing quantity demanded, domestic production, and world price, respectively. The quantity imported from abroad, QT_0, is the difference between demand (Q_D) and domestic production (Q_0). When the supply curve shifts from S_0 to S_1, production increases from Q_0 to Q_1 and imports decrease to

QT_1. Nepal is a small onion importer and does not affect the international price of onions, so price is assumed to be constant. Because price is constant in the model, the economic surplus change is equal to the change in producer surplus ($\Delta TS = \Delta PS = area\ I_0abI_1$). Transport costs and technology spillover are assumed to be zero.

4.4.3 Government Policies

It is important to identify any government policies in the research area that distort output and input prices because they can affect the distribution of the technology-induced benefits (Alston et al., 1995). However, Nepal has not employed restrictive policies such as price-fixing schemes, quantitative restrictions, or exchange-rate distortions. Therefore, the simple closed (for tomato, cauliflower, cucumber) and small open economy (for onion) models are appropriate.

4.5 Calculating Economic Benefits:

As discussed previously, the steps in the economic surplus analysis involve calculating the supply shift and collecting market-related data to estimate IPM's total costs and benefits, net present value, and internal rate of return (Alston et al., 1995). The necessary calculations in the process are presented below.

The supply or K-shift is calculated mathematically as,

$$(3) \quad K = \left(\frac{E(Y)}{\epsilon} - \frac{E(C)}{1 + E(Y)}\right) pA_t$$

where E(Y) is the expected proportionate yield change, $E(C)$ is the expected proportionate cost change, ϵ is the elasticity of supply, p is the probability of research success, and A_t is the adoption rate relative to years, t, from the start of the research program (Alston et al., 1995). For a closed economy model, the change in price relative to the initial value is

$$(4) \qquad Z = \frac{K\,\epsilon}{(\epsilon + n)}$$

In a closed economy model with linear supply and demand and a parallel technology-induced supply shift (or K-shift), the formulas below are used to calculate the change in total surplus (ΔTS), consumer surplus (ΔCS), and producer surplus (ΔPS):

$$(5) \qquad \Delta TS = \Delta CS + \Delta PS = P_0 Q_0 K(1 + 0.5Z\eta)$$
$$(6) \qquad \Delta CS = P_0 Q_0 Z(1 + 0.5Z\eta)$$
$$(7) \qquad \Delta PS = P_0 Q_0 (K - Z)(1 + 0.5\eta)$$

where P_0 and Q_0 are the base price and quantity and η is the (absolute) value of the elasticity of demand (Alston et al., 1995).

For a small open economy model with linear supply and demand and a parallel technology-induced supply shift, the research benefits are calculated as,

$$(8) \qquad \Delta \text{PS} = \Delta TS = PQ_0 K(1 + 0.5K\epsilon)$$

which is found by taking the limit of equation (7) as the demand elasticity approaches infinity and the change in world price, Z, is zero (Alston et al., 1995).

The above formulas can be used to calculate the stream of benefits over a number of years (Alston et al., 1995). The net present value (NPV) of the discounted benefits and cost is calculated as:

$$(9) \quad \text{NPV} = \sum_{t=1}^{n} \frac{B_t - C_t}{(1+i)^t}$$

where B_t = benefits (change in total surplus) in year t, C_t = cost in the year t, and i = discount rate (Alston et al., 1995). The internal rate of return, or IRR, is the interest rate that makes the net present value equal to zero. It can be calculated using the below formula.

$$(10) \quad 0 = \sum_{t=1}^{n} \frac{B_t - C_t}{(1+IRR)^t}$$

To calculate the stream of benefits (NPV) and IRR using IPM technologies, we needed to collect the necessary data, which included:

1. For K-shift:
    a. E(Y): Expected proportionate yield change
    b. E(C): Expected proportionate cost change
    c. Probability of research success
    d. Adoption rates relative to the years from the start of the research program
    e. Elasticity of supply
2. Market-related data:
    a. Price
    b. Production
    c. Elasticity of demand
    d. Exogenous output change
3. For NPV:
    a. Program costs
    b. Discount rate

Once we obtained above data, we entered it into an excel spreadsheet to calculate the economic benefits of using IPM technologies to Surkhet and Banke. The format of the excel spreadsheet we used can be found on page 384 of *Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting* (Alston et al., 1995).

4.6 Data for Economic Surplus Assessment

1. Base Price

iDE Nepal provided us estimates of the monthly prices Nepali vegetable farmers received in the Kohalpur market during the years 2015-2017. Both Banke and Surkhet farmers sell their crops at the Kohalpur market, so we used this price for both districts' surplus analysis. We used the average vegetable price over a 3-year period and the average exchange rate (from January 1, 2015, to December 31, 2017) to convert the Kohalpur market prices from Nepalese Rupees

(NPR) to US Dollar (USD). The exchange rates were obtained from IMF's monthly database (International Monetary Fund, 2021b). The base prices (in USD/Metric tonne) are $363 for tomatoes, $477 for cauliflower, $562 for onions, and $440 for cucumbers.

2. Exogenous Output Change

The exogenous output change is the anticipated proportionate change in output not due to technology adoption or research in each year (Alston et al., 1995). It can be calculated by summing the growth rates of yield and area. In the model, it is used to adjust production (Q_t) in year t,

$$(11) \quad Q_t = Q_0(1+\theta)^t$$

where Q_0 is the base quantity and θ is the exogenous output change. For this study, we used a standard metric of 1%.

3. Base Production

To obtain the base vegetable production values, we used data from the annual publication *Statistical Information on Nepalese Agriculture* (Ministry of Agriculture and Livestock Development, 2021). The 3-year average (2015-2017) production of tomatoes, cauliflowers, onions, and cucumbers in Banke and Surkhet were used as the base production levels in Metric tonnes (Mt). In Banke, the base quantity for each crop is 8,545 Mt for tomatoes, 11,314 Mt for cauliflowers, and 5,876 Mt for onions. In Surkhet, the base production is 3,169 Mt for tomatoes, 2,672 Mt for cauliflower, 1,953 Mt for onion, and 3,321 Mt for cucumber.

4. Program Costs

Leaders in the FTFNIPM program estimated total program costs to be $60,000 for each district, or $20,000 each year for the first three years of the IPM program. Since this is a general figure and not specific to the individual districts, it may be an overestimate. Therefore, we calculated the NPV without including program cost.

5. Elasticity of Supply

The (long-run) elasticity of supply is defined as the percent change in output in response to a percent change in the product price (Nicholson & Snyder, 2012). Agricultural goods typically have inelastic (i.e., less than one) supply in the short run because farmers cannot easily substitute one crop for another after it has been planted. In the long run, however, farmers have greater ease of substitutability regarding farm inputs and production costs, so most agricultural products have elastic (i.e., greater than 1) long-run supply. Unfortunately, we were unable to find any recent research that estimated the elasticities of supply for tomato, cauliflower, onion, and cucumber in Nepal. Alston et al. (1995) suggest that when credible information is not available, it is reasonable to assume 1.0 for the elasticity of supply. Therefore, we assumed a unit elastic supply of 1.0 for all vegetables.

6. Elasticity of Demand

The (own) price elasticity of demand is a unit-free measurement of the proportionate change in quantity demanded that results from a proportionate change in a good's own price (Nicholson & Snyder, 2012). To obtain the elasticity of demand for our analysis, Alston et al. (1995) recommend using published results from past research studies. Using a 2003 cross-sectional study found from the USDA's Economic Research Service website, we assumed the own-price elasticity of demand for tomato, cauliflower, and cucumber in Nepal to be -0.522 (Seale Jr. et al., 2003). For onion, the elasticity of demand is assumed to be infinite because Nepal relies on imports for consumption but is only a small importer in the global market.

7. Discount rate

When benefits and costs are calculated in constant value, the discount rate should be the (real) rate of interest, adjusted for inflation, and generally falls between 3-5% (Alston et al., 1995). We will use a 5% discount rate, which is standard in adoption studies (Myrick et al., 2014; Rahman et al., 2018).

8. Expected proportionate yield and cost changes

To calculate yield and cost changes using IPM practices, we used partial budgets from field trials conducted by iDE Nepal in 2019. Field crop trials were performed for *four* vegetables (tomato, cauliflower, onion, and cucumber) in Surkhet and for *three* vegetables (tomato, cauliflower, and onion) in Banke. The field trials took place in two different districts with distinct climate conditions; Banke is lower tropical with hot summers, and Surkhet is upper tropical with heavy rain seasons and cooler temperatures. The farmers in these two districts may use different pest management products based on the pest incidence in their area. Because the farmers in the trials had different levels of input usage and choice of pest management products, we conduct two separate economic impact analyses for each district.

In the field trials, farmers cultivated vegetables on two different plots of land. On one plot, they used IPM methods (biopesticides and traps) to prevent and control pests. For the control (non-IPM) plot, they used regular farming practices (synthetic pesticides) to manage pests. In both districts, tomatoes and cauliflowers were grown on 333 m^2 plots. Similarly, cucumbers were grown on 333 m^2 plots in Surkhet. Onions were grown on 50 m^2 plots in both districts. In Banke, data were collected from four tomato farmers (n = 4), four cauliflower (n = 4), and three onion farmers (n =3). In Surkhet, data were collected from three tomato, three cauliflower, three onion, and three cucumber farmers, so the sample size was n = 3 for each.

For each variable input used, data were collected on the use, unit, rate per unit, and cost in Nepalese rupees (NPRs), which was used to calculate total cost. Inputs included seed, IPM practices, labor, pesticides, and additional vegetable-specific inputs (e.g., micronutrients for onion farmers). The IPM practices used on each plot were cultural methods, biopesticides, and pheromone traps. In addition, data were collected on the total production on each plot. We used the average cost and yield from the vegetable farmers to compare the total cost (in US dollars per hectare) and total yield (in kilograms per hectare) using IPM methods and non-IPM methods for each vegetable in the two districts. The results are shown below.

Table 4.2 Field trial results*

Crop	BANKE		SURKHET	
	Cost (USD/ha)	**Yield (kg/ha)**	**Cost (USD/ha)**	**Yield (kg/ha)**
Tomato				
IPM Plot	$2,253	54,535	$1,849	52,553
Non-IPM Plot	$2,766	50,420	$1,931	51,502
Cauliflower				
IPM Plot	$1,946	30,961	$1,442	32,673
Non-IPM Plot	$2,007	27,748	$1,624	30,691
Onion				
IPM Plot	$4,376	25,800	$4,829	22,600
Non-IPM Plot	$4,004	22,000	$5,425	20,800
Cucumber				
IPM Plot			$1,978	26,787
Non-IPM Plot			$2,069	24,925

For the economic surplus analysis, we were interested in finding the change in yield, E(Y), and change in cost, E(C), using IPM methods compared to non-IPM (chemical) methods. The expected proportionate yield change per hectare, E(Y), was calculated using the following formula,

$$(12) \qquad E(Y) = \frac{Y_{IPM} - Y_{Non-IPM}}{Y_{Non-IPM}}$$

*1 Hectare = 10,000 m^2 = 2.47 Acres = 19.66 Ropani
1 Kilogram = .001 Metric Ton = 2.2046 lbs

where Y_{IPM} is the average yield using IPM practices and $Y_{Non-IPM}$ is the average yield using non-IPM (chemical) practices. The expected proportionate cost change, E(C), was calculated using the following formula,

$$(13) \qquad E(C) = \frac{TC_{IPM} - TC_{Non-IPM}}{TC_{Non-IPM}}$$

where TC_{IPM} is the average total cost using IPM practices and $TC_{Non-IPM}$ is the average total cost using non-IPM practices. The results from these calculations are presented below.

Table 4.3 Yield and cost change results

Crop	**Banke:**		**Surkhet:**	
	E(Y)	*E(C)*	*E(Y)*	*E(C)*
Tomato	8%	– 19%	2%	– 4%
Cauliflower	12%	– 3%	7%	– 11%
Onion	17%	9%	9%	– 11%
Cucumber	-	-	7%	– 4%

In **Surkhet**, when tomato and cucumber farmers used IPM methods instead of relying solely on synthetic pesticides, their total costs decreased by 4%. For cauliflower and onion farmers, using IPM methods cost 11% less than using synthetic pesticides alone. When cauliflower and cucumber farmers used IPM products rather than solely using synthetic pesticides, their yields increased 7%. Tomato farmers that used IPM practices had a 2% increase in yield. Lastly, when onion farmers used IPM methods, their yield increased by 9%.

In **Banke**, when tomato farmers used IPM practices instead of synthetic pesticides, their total cost decreased by 19% and yield increased by 8%. For Banke cauliflower farmers, using IPM methods rather than synthetic pesticides alone reduced cost by 3% and increased yield by 9%. While using IPM methods increased total cost for onion farmers by 9%, it also increased their yield by 17%.

A limitation of the field trials was that participants were not randomly selected. Also, because experimental results do not always equate to everyday environment, the costs and returns for regular farmers may differ from those found in the field trials. Lastly, the trials had sample sizes of either three or four observations per vegetable in each district, so we could not perform statistical analyses.

9. Probability of research or technology success

The probability of research success is the probability that research will achieve the expected yield change (Alston et al., 1995). Because we are not predicting E(Y) based on expert opinion and will use results from successful experimental field trials, the probability of success was 100%.

10. Adoption rates

In the field trials, the farmers used a combination of complex IPM methods on their IPM plots. To be consistent in our economic impact analysis, we defined adoption as using 1) non-synthetic (naturally-occurring) pesticides **and** 2) pheromone traps. This definition differs from adoption in the econometric adoption model in Chapter 3, which defined adoption (the dependent variable) as using biopesticides **or** pheromone traps. Because fewer farmers adopted both biopesticides and pheromone traps, the adoption rates for this analysis are lower. For this analysis, the adoption rate is a proxy for land area of IPM under those crops.

The two most common functional forms used in adoption studies are linear (as part of the trapezoidal lag structure) and sigmoid, or logistic, curve (Alston et al., 1995). In a sigmoid curve, the aggregate adoption rate is initially slow with a few adopters, then accelerates to a maximum rate, and finally increases at a slower rate until it reaches the maximum adoption rate (Rogers, 1983). Rogers (1983) argues that as information about the technology is exchanged between peer networks, adoption will spread and increase exponentially. Because farmers often rely on members of their social system for knowledge and advice on new practices or products, we believe the sigmoid structure is more suitable for this study. Alston et al. (1995) define the sigmoid structure as

$$(14) \qquad A_t = \frac{A^{MAX}}{1 + e^{-(\alpha + \beta t)}}$$

where A_t is the adoption rate t years after the start of the program or release of the technology. A^{MAX} is one of the three parameters, defined as the technology's maximum adoption rate. The other two parameters are α and β that define the adoption path as it approaches the asymptote A^{MAX}(Alston et al., 1995). To elicit the values of α and β, two points on the curve are needed. For this analysis, one point was the first year's adoption rate, which we assume to be as close to zero as possible, so A_1 = 0.001. We used the survey adoption rate of using both pheromone traps and biopesticides for the second point, which in our model is A_7, seven years after research started. The last piece of the required information is A^{MAX}, which we assumed to occur in 2026 and will be 10% greater than the 2021 survey adoption rate. Once the two adoption points and A^{MAX} are obtained, the α and β parameters can be calculated using the equation below for each point and then setting them equal to each other to find α (Alston et al., 1995).

$$(15) \qquad \beta = \left[ln\left(\frac{A_t}{A^{MAX} - A_t}\right) - \alpha \right] * \frac{1}{t}$$

Using A_1 and A_7, we developed adoption profiles for the three vegetables in Banke and the four vegetables in Surkhet and used these adoption rates in the economic surplus calculation. The necessary parameters used for the economic surplus are listed below.

Table 4.4 Parameters for economic surplus model

Parameters	Banke			Surkhet			
	Tomato	**Caul.**	**Onion**	**Tomato**	**Caul.**	**Onion**	**Cuc.**
Type of Economy	*Closed*	*Closed*	*Small open*	*Closed*	*Closed*	*Small open*	*Closed*
Supply elasticity	1	1	1	1	1	1	1
Demand elasticity	– 0.52	– 0.52	∞	– 0.52	– 0.52	∞	– 0.52
Yield change (%)	8%	12%	17%	2%	7%	9%	7%
Production cost change (%)	– 19%	– 3%	9%	– 4%	– 11%	– 11%	– 4%
Max adoption rate	17.5%	14.8%	11.6%	22.2%	24.8%	11.9%	30.5%
Base price (US$/Metric tonne)	$363	$477	$562	$363	$477	$562	$440
Base quantity (Metric tonnes)	8,545	11,314	5,876	3,169	2,672	1,953	3,321
Probability of research success	100%	100%	100%	100%	100%	100%	100%
Exogenous growth in supply	1%	1%	1%	1%	1%	1%	1%
Discount rate	5%	5%	5%	5%	5%	5%	5%

Chapter 5. Results

5.1 Extent of Vegetable Adoption

Out of the 346 vegetable farmers surveyed, 70% adopted at least one IPM practice. While 70% IPM adoption is promising, we wanted to distinguish between simple IPM practices that are commonly used on any farm and more complex practices that typically require more knowledge and conscious use of IPM itself. Therefore, IPM practices were categorized into two categories: simple and complex. Complex practices included pheromone traps and biopesticides (e.g., neem products, *Trichoderma*, and *Pseudomonas*). Of the 243 farmers that used at least one IPM practice, 117 used at least one simple practice and no complex practices, and 126 used at least one complex IPM practice. For the 126 complex-practice adopters, the most used practice was pheromone traps for tomato and cucumber farmers and neem products for cauliflower and onion farmers.

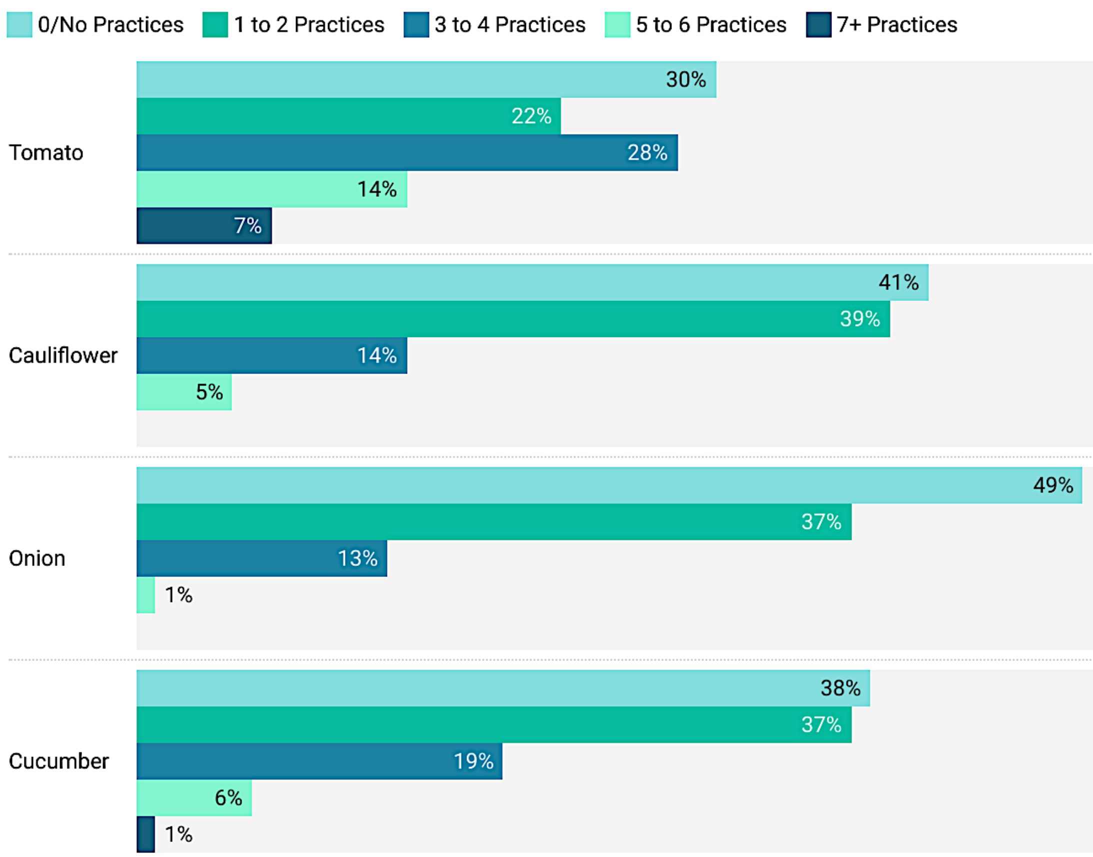
Table 5.1 Most used simple and complex IPM practices

Type of Practice	Tomato	Cauliflower	Onion	Cucumber
Simple	Remove damaged plants (58%)	Remove damaged plants (48.3%)	Remove damaged plants (38.3%)	Remove damaged plants (44.9%)
Complex	Pheromone trap (17.4%)	Neem products (18.6%)	Neem products (10.4%)	Pheromone trap (21.3%)

Figure 5.1 shows the percentage of farmers who adopted zero, one to two, three to four, five to six, and more than seven IPM practices. In the questionnaire, tomato farmers could list up to 15 IPM practices used from net-house or open field/polyhouse production methods, up to 11 for cauliflower farmers, up to 11 for onion farmers, and up to 10 for cucumber farmers. Tomato

farmers adopt the greatest number of IPM practices (seven or more), but respondents also had the most (15) practices to choose from. On average, an individual vegetable farmer uses 2.5 IPM practices if they grow tomatoes, 1.3 practices if they grow cauliflowers, 0.95 practices if they grow onions, and 1.6 practices if they grow cucumbers.

Figure 5.1 Count of all IPM practices



A 2018 survey of tomato farmers (conducted by FTF) in Nepal found IPM adoption rates quite different from ours. In 2018, only 5.25% of tomato farmers were non-adopters and over 50% used biopesticides (Knaresboro, 2019). Comparatively, our 2021 survey found that 30% of tomato farmers were non-adopters and only 14% used biopesticides. This decline in adoption rates could be due to a variety of factors such as differences in the sample sizes or the questionnaire format. In addition, adoption rates could have been affected by the ongoing

COVID-19 pandemic and resulting economic downturn. While we tried to incorporate some impacts, including access to inputs during the pandemic that could directly influence the adoption process, it is too early to ascertain the full extent that the COVID-19 pandemic has had on farm households and their IPM adoption decisions.

5.2 Determinants of IPM Adoption

In our econometric adoption model, we defined complex adopters as those who used either 1) pheromone traps or 2) biopesticides. Biopesticides (e.g., neem products, *Trichoderma,* and *Pseudomonas)* are non-toxic pesticides that use natural products (such as plant extracts and microorganisms) to control pests. In our model, 33% of tomato farmers, 25% of cauliflower farmers, 12% of onion farmers, and 33% of cucumber farmers were complex adopters. "Non-adopters" include simple adopters and those who did not use any IPM practices. Table 5. 2 displays summary statistics for the characteristics of complex adopters and non-adopters for each vegetable in our survey.

In general, differences between complex adopters and non-adopters differ by vegetable. However, across the four vegetables, higher portions of non-adopters experience medium or high pest severity than complex adopters indicating that using complex IPM practices lowers pest incidence. However, since pest severity could be endogenous, we cannot determine if using complex IPM practices negatively or positively affects pest severity. The average age of non-adopters is 41 for tomato and cucumber, 39 for cauliflower, and 40 for onion. For tomato, onion, and cucumber farmers, 30% of non-adopters never attended school. For cauliflower farmers, 21% of non-adopters never attended school. Across all vegetables, non-complex adopters had a larger percentage of female primary decision makers than complex adopters.

The average age of complex adopters is 41. Compared to non-adopters, a greater portion of complex adopters are male. On average, a larger percentage of complex adopters have higher education levels (college and SLC completion). Out of all complex adopters, 15% of tomato and cucumber, 18% of onion, and 19% of cauliflower farmers have no schooling. On average, complex adopters live further away from an agro-vet than non-adopters. A greater portion of complex adopters receive advice from a community business facilitator (CBF) than non-adopters. A larger proportion of cucumber and tomato complex adopters are members of a farm or community organization than non-adopters. Except for onion, complex adopters have more farming experience. Across all vegetables, most complex adopters are trained in IPM and live in a village with more than 50% of surveyed farmers trained in IPM.

Table 5.2 Summary statistics by adoption group

Variables	**Tomato** (Mean or %)		**Cauliflower** (Mean or %)		**Onion** (Mean or %)		**Cucumber** (Mean or %)	
	Com. Adopter	*Non-adopter*	*Com. Adopter*	*Non-adopter*	*Com. Adopter*	*Non-adopter*	*Com. Adopter*	*Non-adopter*
Adopt IPM	33%	67%	25%	75%	12%	88%	33%	67%
Age (years)	41	41	41	39	41	40	41	41
Number of farmworkers in household	3.02	3.25	3.18	2.94	3.23	3.24	3.39	3.13
Migrant in the household	23%	32%	22%	27%	41%	32%	27%	24%
Distance to an agro-vet (km)	4.06	3.34	3.83	3.43	3.76	3.70	4.08	3.01
Distance to an extension office (km)	5.15	4.66	4.84	4.73	4.32	4.97	4.97	4.27
Farming Experience	11.65	13.61	12.60	11.61	13.36	13.38	14.24	12.30
Land farmed (Ropani)	12.50	11.89	12.49	10.88	11.42	12.07	13.46	10.47
Member of farm organization	86%	83%	81%	82%	77%	81%	90%	82%
No education	15%	30%	19%	21%	18%	30%	15%	30%

Primary education	28%	29%	28%	27%	36%	25%	29%	24%
Secondary education	22%	21%	19%	29%	18%	22%	22%	24%
SLC or college education	35%	20%	33%	23%	27%	23%	34%	21%
Severe pest damage last year	31%	46%	22%	35%	18%	24%	29%	40%
Advice from CBF	29%	15%	33%	16%	27%	12%	34%	13%
Access to inputs during COVID	58%	50%	52%	54%	55%	52%	53%	55%
Female	49%	64%	49%	67%	55%	70%	42%	65%
Surkhet district	35%	20%	33%	20%	23%	29%	25%	20%
Banke district	26%	38%	33%	31%	36%	34%	29%	18%
Kanchanpur district	17%	28%	16%	26%	27%	25%	15%	34%
Kavre district	22%	14%	18%	23%	14%	12%	31%	27%
High caste	65%	55%	63%	57%	59%	60%	63%	61%
Middle caste	32%	37%	28%	37%	32%	34%	29%	34%
Low caste	3%	8%	9%	6%	9%	7%	8%	6%
Proportion of village trained in IPM	0.56	0.45	0.59	0.46	0.56	0.46	0.55	0.42
IPM training	74%	43%	73%	44%	86%	39%	76%	37%
Number of obs.	195		263		183		178	

5.2 Factors Influencing the Decision to Adopt

To analyze the defining factors affecting Nepali farmers' decision to adopt complex IPM practices, a probit model was run for each vegetable. The *vce(robust)* command, formally known as the Huber/White/sandwich estimator, was used to adjust standard errors for potential heteroskedasticity (StataCorp, 2021a). In the table, "Prob > chi2" is the p-value, or smallest significance level at which the null hypothesis can be rejected, for the Likelihood Ratio (LR) Chi-Square test (Wooldridge, 2013). The null hypothesis for the LR test is that the regression coefficients are simultaneously equal to zero (UCLA: Statistical Consulting Group, 2021). Each vegetable's regression has a p-value less than the significance level ($\alpha = 0.05$), so we reject the null hypothesis. The results are shown in Table 5.3 below.

Table 5.3 Probit regression results

	Tomato Number of obs. = 195 Prob > chi2 = 0.004		**Cauliflower** Number of obs. = 263 Prob > chi2 =0.000		**Onion** Number of obs. = 183 Prob > chi2 =0.007		**Cucumber** Number of obs. = 178 Prob > chi2 = 0.000	
Variables	*Coef.*	*dy/dx*	*Coef.*	*dy/dx*	*Coef.*	*dy/dx*	*Coef.*	*dy/dx*
Age	0.001	0.000	0.005	0.001	0.022	0.003	**-0.029****	**-0.008****
Farmworkers	0.000	0.000	0.070	0.021	-0.054	-0.008	-0.026	-0.007
Migrant in the household	-0.138	-0.040	-0.081	-0.024	**0.587***	**0.090***	0.355	0.096
Distance to an agro-vet	0.040	0.012	0.011	0.003	0.022	0.003	**0.148*****	**0.040*****
Distance to an extension office	-0.004	-0.001	-0.026	-0.008	-0.043	-0.006	-0.059	-0.016
Farming Experience	-0.017	-0.005	-0.017	-0.005	-0.032	-0.005	**0.025***	**0.007***
Land farmed	-0.001	-0.000	-0.002	-0.001	-0.004	-0.001	0.013	0.003
Member of farm organization	-0.180	-0.053	-0.280	-0.087	-0.328	-0.051	0.213	0.056
Primary education	-0.125	-0.034	-0.293	-0.091	**0.830***	**0.127***	0.157	0.042
Secondary education	0.245	0.072	-0.360	-0.109	0.139	0.016	-0.030	-0.008
SLC or college education	0.472	0.142	-0.188	-0.060	0.299	0.037	0.347	0.095
Severe pest damage	**-0.546****	**-0.156****	-0.288	-0.083	-0.425	-0.056	-0.424	**-0.111***
Advice from CBF	0.045	0.013	-0.062	-0.018	**0.790****	**0.137***	0.412	0.117
Access to inputs	0.334	0.096	0.225	0.066	0.275	0.039	0.117	0.031
Female	-0.283	-0.084	**-0.545*****	**-0.170*****	**-0.774****	**-0.121****	**-0.678****	**-0.188*****
Banke district	**-0.514***	**-0.148***	-0.170	-0.048	0.374	0.043	0.271	0.067
Kanchanpur district	-0.246	-0.074	0.219	0.069	**1.053****	**0.157****	0.049	0.012
Kavre district	0.237	0.075	-0.078	-0.023	0.733	0.097	**0.865****	**0.231*****
Middle caste	0.031	0.009	-0.337	**-0.096***	0.150	0.021	0.024	0.006
Low caste	-0.148	-0.042	0.183	0.060	0.586	0.098	**1.039****	**0.291****
IPM training	**1.102****	**0.320****	**1.569*****	**0.432*****	**1.621*****	**0.238*****	**1.065*****	**0.305*****

constant	-0.603	-0.681	**-2.961*** **	-0.925

Omitted group variables: *no education, Surkhet district*, and *High caste*
* = p<0.1, ** = p<0.05, *** = p<0.01

5.3 Discussion of Significant Results

In models with a latent variable, the estimated coefficients for the explanatory variables provide information on the direction of the effect (positive or negative), but they do not provide an interpretation of the effect's magnitude (Wooldridge, 2013). Marginal effects provide predictions on the differences in probabilities by changing the value of the covariate (Perraillon et al., forthcoming). We report the average marginal effects, which are calculated by multiplying the scale factor (average of the individual partial effects across the sample) by the coefficient (Wooldridge, 2013).

Across the four vegetables, IPM training is a positive and significant (at 5% and 1% level) determinant of IPM adoption. Holding all other independent variables constant at their fixed values, IPM training increases the probability of adopting complex IPM practices by 32 percentage points for tomato farmers, 43.2 percentage points for cauliflower farmers, 23.8 percentage points for onion farmers, and 30.5 percentage points for cucumber farmers. These results support our hypothesis that primary decision-makers who have been trained in IPM practices are more likely to adopt complex practices. Except for tomatoes, being a female primary decision-maker negatively affects (significant at 5% and 1%) adoption. Holding all explanatory variables at their fixed values, being a female primary-decision maker decreases the probability of adopting complex IPM practices by 17 percentage points for cauliflower, 12.1 percentage points for onion, 18.8 percentage points for cucumber. Pest severity has a negative effect (significant at the 5% level) on the adoption of complex practices for tomato farmers. For cucumbers, the marginal effect of pest severity is also negative and statistically significant (at 10%). However, as pest damage increases, farmers increase their use of various methods of control such as IPM or chemical pesticides, and pest severity and damage could decrease. Therefore, this result may arise from endogeneity of severity of pest damages in IPM adoption.

For **tomato**, the Banke district variable is a significant factor affecting adoption at 10%. Holding all independent variables constant at their fixed values, the probability of adopting complex IPM practices is higher for tomato farmers living in Banke than Surkhet by 14.8 percentage points.

With **cauliflower**, the average marginal effects for the middle caste group, *midcaste,* has a negative effect (significant at 10%) on adoption of complex practices. The high-caste group, which included Brahmin, Chhetri, Newar, and Thakuri, was the base/omitted group. This result supports our prediction that compared to farmers in the high-caste group, primary decision-makers in the medium-caste group are less likely to adopt complex IPM practices.

For **onion** farmers, compared to no schooling, educational attainment at the primary school level has a positive effect (significant at 10%) on adoption of complex IPM practices. This result supports our predictions that higher education levels increase the primary decision maker's likelihood of adoption. Holding all other independent variables constant at their fixed values, receiving advice from a community business facilitator (CBF) increases the probability of adopting complex IPM practices by 13.7 percentage points. This finding is significant at a 10% level. We speculated that since CBF's help farmers access agricultural inputs that ease possible adoption constraints, receiving advice from CBFs would have a positive relationship with IPM adoption. These results support our initial hypothesis. The presence of a migrant in the household positively affects adoption for onion farmers and is statistically significant at the 10% level. Compared to Surkhet (the base group), living in Kanchanpur has a positive effect (significant at 5%) on the adoption of complex practices.

For **cucumber** farmers, age negatively affects adoption of complex IPM practices and is statistically significant at the 95% confidence interval. These results support the hypothesis that older farmers are more risk-averse, making them less willing to try new technologies.

For cucumber farmers, living in Kavre (compared to Surkhet) positively affects complex IPM adoption. The estimated coefficient is statistically significant at a 5% level and the average marginal effects are significant at a 1% level. For cucumber farmers, compared to members of the high-caste group, being in the low-caste group (Muslim or Dalit) has a positive effect (significant at 5%) on adoption of complex practices. Holding all other explanatory variables constant at their fixed values, the probability of adopting complex IPM practices is 29.1 percentage points higher for members of a low-caste ethnic or caste group than members of a high-caste group. These results conflict with our initial predictions and could indicate that outreach programs have reached lower caste/ethnic groups, increasing their awareness of IPM practices and likelihood of adoption. Severe pest damage is negatively associated with IPM adoption, and the marginal effects are statistically significant at the 10% level. Lastly, for cucumber farmers, distance to an agro-vet positively affects adoption, which means that living further away from an agro-vet positively affects complex IPM practices. This is statistically significant at the 1% level.

5.4 Extended Discussion on IPM Training and Gender

Across the models, we consistently found two explanatory variables to be statistically significant factors affecting complex IPM adoption: gender and IPM training. The only model where gender was not significant was the tomato model.

Of the 346 interviews with household primary-decision makers, 67% were females and 33% were males. From the female-headed households, only 28% adopted complex IPM practices. Comparatively, 53% of the male-headed households adopted complex IPM practices.

Out of all vegetable farm-households, 48% had a household member with IPM training. Households with IPM training attended an average of 1.56 training sessions, and over 75% were trained by a non-governmental organization (NGO) agricultural extension worker. The second and third most common sources of training were government extension workers and community business facilitator (CBFs).

Table 5.4 IPM Training

Source of IPM Training	% of Male-Headed Households	% of Female-Headed Households	% of All Households
Government Extension Worker	37%	24%	28%
Agro-vet	4%	3%	3%
Community Business Facilitator (CBF)	23%	23%	23%
NGO Extension Worker	86%	73%	78%
Other	2%	3%	2%
Total Number of Households	114	232	346

Comparing IPM training by gender of the primary-decision maker, 47% of female-headed households and 50% of male-headed households had a household member with IPM training. A larger portion of male-headed households were trained by government and non-governmental organization (NGO) extension workers than female-headed households. Female-headed households with IPM training attended an average of 1.4 training sessions.

Comparatively, male-headed households with IPM training attended an average of 1.9 training sessions.

5.4 Economic Surplus Results

5.4.1 Results for the Banke District

Table 5.5 shows the undiscounted change in total economic surplus, net economic benefits with and without research costs estimated at $60,000 for each crop, and the distribution of net benefits from using IPM practices for the **Banke** district. As seen in the table, the net benefits without research costs are equal to the change in total surplus. The cash flows are undiscounted because they have not been adjusted for the time value of money (using a 5% discount rate). The cumulative undiscounted net benefits without costs for Banke are $1.4 million. When we account for research costs, the cumulative total economic benefits are $1.28 million. The benefits of IPM practices are derived from the yield increases and reduced synthetic pesticide costs. Because of the large supply shift from yield and cost changes, one-half of the benefits are from using IPM in tomato production.

Because supply is assumed to be unit-elastic, cauliflower and tomato consumers benefit more than producers. Because Nepal heavily imports onions and is assumed to be a small country in trade, all benefits accrue to producers. Lower adoption rates result in fewer benefits in onions.

Table 5.5 Undiscounted Net Benefits in Banke

Banke						
Crop	**Change in Producer Surplus**	**Change in Consumer Surplus**	**Change in Total Surplus**	**Total Research Cost (C)**	**Net benefit**	**Net benefit w/o Costs (C=0)**
Tomato	$269,718	$516,276	$785,993	$60,000	$725,993	$725,993
Cauliflower	$200,569	$383,916	$584,486	$60,000	$524,486	$584,486
Onion	$93,307		$93,307	$60,000	$33,307	$93,307
Total	$563,594	$900,192	$1,463,786	$180,000	$1,283,786	$1,403,786

5.4.2 Results for the Surkhet District

Table 5.6 shows the undiscounted benefits for the four crops in Surkhet. Using the surplus approach, the total undiscounted net benefits for Surkhet are $868,520. When we account for research costs, the undiscounted benefits are $628,520. Over 90% of benefits are in cauliflower and cucumber. Benefits from using IPM in tomato production in Surkhet are smaller than IPM tomato production in Banke due to lower yield and cost changes. Because onion farmers had lower adoption rates, total benefits are lower compared to the other vegetables in Surkhet. Nepal is considered a small-open economy with respect to onions, so all benefits accrue to producers. Because of the unit-elastic price elasticity of supply, tomato, cauliflower, and cucumber consumers benefit more than producers.

Table 5.6 Undiscounted Net Benefits in Surkhet

Surkhet						
Crop	Change in Producer Surplus	Change in Consumer Surplus	Change in Total Surplus	Total Research Cost (C)	Net benefit	Net benefit w/o Costs (C=0)
Tomato	$33,909	$65,209	$99,118	$60,000	$39,118	$99,118
Cauliflower	$119,272	$228,302	$347,573	$60,000	$287,573	$347,573
Onion	$75,351	-	$75,351	$60,000	$15,351	$75,351
Cucumber	$118,896	$227,582	$346,478	$60,000	$286,478	$346,478
Total	$347,427	$521,093	$868,520	$240,000	$628,520	$868,520

5.4.3 NPVs and IRRs

The net present values (NPV) and internal rate of returns (IRR) for the three crops in Banke and four crops in Surkhet are presented in Table 5.7. We calculated the net present values by discounting the net benefits at a discount rate of 5%.

With the surplus approach, the present value of total benefits from IPM use for the three crops in **Banke** is $920,753. When we include research costs, the present value of benefits changes to $757,358.

The cumulative present value of benefits from IPM adoption for the four vegetables in **Surkhet** is $521,696. When we include research costs, the present value of benefits is $303,836. When research costs are included, the NPV for onions in Surkhet is negative. However, since we suspect that research costs of $60,000 per vegetable may be an overestimate, this is not particularly concerning.

The sum of the present value of benefits for the two districts is $1.44 million. When costs are accounted for, the cumulative present value of the two districts' benefits is $1.06 million.

Table 5.7 Discounted benefits for Banke and Surkhet

Crop	Banke			Surkhet		
	NPV (No Research Cost)	NPV (C = $60,000)	IRR (%)	NPV (No Research Cost)	NPV (C = $60,000)	IRR (%)
Tomato	$496,405	441,940	47%	$63,098	$8,633	7%
Cauliflower	$366,272	$311,807	39%	$221,813	$167,348	30%
Onion	$58,076	$3,611	6%	$46,884	-$7,581	3%
Cucumber	-	-	-	$189,901	$135,436	28%
Total	$920,753	$757,358	-	$521,696	$303,836	-

5.5 Sensitivity Analysis

Because the nature of the parameters (e.g., maximum adoption rate) is uncertain, researchers often use sensitivity analysis to indicate the robustness of the results (Alston et al., 1995). A sensitivity analysis involves testing different values, from either a range of values (high, middle, low) or a viable alternative for the uncertain parameters to see how the projected benefits change. From there, we can judge which parameters our model results are most sensitive to. Because program costs may have been overestimated, we performed our sensitivity analysis by looking at changes to total benefits without research costs. We chose to test the sensitivity of our results to changes in the A^{MAX} and elasticity of demand. For the low ranges of adoption, we tested rates that were 5% lower than the initial maximum adoption rate (e.g, 10% to 5%). For the high ranges of adoption, we increased the initial maximum adoption rates by 5% (e.g, 10% to 15%). For elasticity of demand, we increased and decreased the initial values by 50% to determine how total benefits and the distribution of benefits to consumers and producers change.

5.5.1 Adoption Rate

When we tested the low and high values for maximum IPM adoption rate for tomatoes in **Surkhet**, the net present values of benefits are projected to be $55,017 to $71,175. Using the same methods, the IPM benefits cauliflower in Surkhet are projected to be $197,042 to $247,355. For onions, the range is $38,575 to $52,234. Lastly, the IPM benefits in Surkhet for cucumber are $176,806 to $204,768. The cumulative present value of benefits for the four vegetables in Surkhet ranges from $467,440 to $ $575,532.

For **Banke**, when we tested high and low IPM adoption rates for the three vegetable crops, the range of benefits is projected to be $ $418,836 to $577,304 for tomato, $290,714 to $433,973 for cauliflower, and $48,697 to $63,686 for onion. The cumulative present value of benefits for the three vegetables in Surkhet ranges from $758,247 to $ $1,074,963.

The cumulative preset value of benefits, not including costs, across the two districts ranges from $1.22 million to $1.65 million. Since the supply shift is dependent on the adoption rate, raising the maximum adoption rates increases the supply shift (K-shift). With the high maximum adoption rates, the equilibrium price is lower, equilibrium quantity is higher, and total benefits are greater. Lowering the maximum adoption rates results in a smaller K-shift. Because equilibrium price and quantities change by a lesser extent, net benefits for consumers and producers are lower. Because we previously assumed a parallel shift in supply in a closed economy for tomato, cauliflower, and cucumber, changes to total benefits are distributed equally among producers and consumers. Since Nepal largely imports onion and is considered a small economy, all benefits accrue to producers.

5.5.2 Elasticity of demand

For onions, we assumed a small open economy model with infinitely elastic demand. Because the economic surplus change is all producer surplus, only the elasticity of supply changes total benefits.

For tomato, cauliflower, and cucumber, we assumed an absolute value of the elasticity of demand to be 0.52. When we increased the initial demand elasticity by 50%, there was only a slight increase (less than 1%) in total benefits, but the distribution of total benefits significantly changed. When consumers are more responsive (in terms of quantity demanded) to changes in price, consumer surplus is less. When demand is more elastic, benefits reallocate from consumers to producers.

When we decreased the elasticity of demand by 50% for tomato, cauliflower, and cucumber, total benefits slightly decrease (less than 1%), but the distribution of benefits to consumers increase. At a more inelastic demand, benefits reallocate from producers to consumers.

Chapter 6. Conclusion

The two primary objectives of this study were to

1. Determine the extent of IPM adoption for high-value Nepali vegetable farmers, and assess the factors that affect their decision to adopt
2. Compare the financial and economic performance of IPM practices on vegetables (tomato, cauliflower, onion, and cucumber) to conventional pest management practices.

6.1 Summary

6.1.1 Objective 1

To achieve Objective 1, we constructed and implemented a survey in four districts (Surkhet, Banke, Kanchanpur, and Kavrepalanchok) of Nepal during the period of March to April 2021. The complete survey provided cross-sectional data on household demographics, IPM knowledge and sources, farm characteristics, seedbed and land preparation, crop establishment, fertilizer application, pest management, and production and disposal. 400 households were selected for the survey, and interviews were conducted with the household's primary decision-maker or the person who makes (solely or jointly with a spouse) decisions regarding pest management on the farm.

Fifty-one observations were removed because the respondents had not grown vegetables in the past year. Two observations were removed because they were duplicates, and one was removed because the survey was incomplete. Of the remaining 346 vegetable farmers surveyed, 195 grew tomatoes, 263 grew cauliflowers, 183 grew onions, and 178 grew cucumbers.

Out of the 346 vegetable farmers surveyed, 70% adopted at least one IPM practice. While 70% IPM adoption is promising, we wanted to distinguish between simple IPM practices that are commonly used on any farm and more complex practices that typically require more knowledge and the conscious use of IPM practices. Therefore, IPM practices were categorized into two categories: simple and complex. Complex practices included pheromone traps and biopesticides. Sixty-nine percent of farmers adopted a simple IPM practice. Of the 243 farmers that used at least one IPM practice, 239 used at least one simple practice, and 126 used at least one complex IPM practice. For the 126 complex-practice adopters, the most used practice was pheromone traps for tomato and cucumber farmers and neem products for cauliflower and onion farmers. The most common simple practice across all vegetable farmers was the removal of infected plants.

Once we examined the extent of IPM adoption by Nepali vegetable farmers, our next objective was to determine if specific factors influence IPM adoption. To do this, we used a probit model with a binary dependent variable for adoption. The binary adoption variable was defined as one for complex-practice adopters and zero for simple-adopters and non-adopters. Explanatory variables included individual characteristics of the household's primary decision-maker, geographic variables, other miscellaneous variables we suspected might influence adoption of complex IPM practices. In our results, two explanatory variables consistently affect complex IPM adoption: gender and IPM training.

IPM training is found to be a positive and significant determinant of adoption of a complex IPM practice. The results support our hypothesis that primary decision-makers who have been trained in IPM practices are more likely to adopt complex practices. Out of all vegetable farm-households, 48% had a household member with IPM training. Households with IPM training attended an average of 1.56 training sessions, and over 75% were trained by an NGO agricultural extension worker.

Except for tomato farmers, our findings indicate that being a female primary decision-maker had a significant negative effect on adoption of complex IPM practices. Of the 346 interviews with household primary-decision makers, 67% were females and 33% were males. From the female-headed households, only 28% adopted complex IPM practices. Comparatively, 53% of the 114 male-headed households adopted complex IPM practices.

In Nepal, women have less access to finance and market facilities, land ownership, and bargaining power (FAO, 2019). In addition, Nepal's government policies have focused more on increasing female participation in programs and projects than on policies or strategic interventions to address gender inequality, which affects women's livelihoods and empowerment (FAO, 2019). Any or all of these factors could affect why female-headed households are less likely to adopt complex IPM technologies. To increase adoption of complex IPM practices by female-headed households, programs may consider developing dissemination strategies that promote gender equality and rural women's empowerment. Future research could look at the differential impacts of training on females, and the pathways in which being a female primary decision maker can lower complex IPM adoption.

6.1.2 Objective 2

To compare the economic performance of IPM to conventional pest management practices, we used partial budgets from field trials, adoption rates from the 2021 survey, and market data to estimate the cumulative IPM benefits using an economic surplus approach. For this analysis, we defined IPM adoption as using both biopesticides and pheromone traps.

The field trials were conducted for three vegetables in Banke and four vegetables in Surkhet. Each farmer in the trial grew a vegetable on two plots of land, where they employed IPM practices on one plot and synthetic pesticides on the other plot. In Banke, the sample size was three farmers for onions and four farmers for both cauliflower and tomato. In Surkhet, the sample size was three farmers for each vegetable (tomato, cauliflower, onion, and cucumber).

In Banke, the total cost of producing tomatoes and cauliflowers using IPM methods was less than producing using conventional synthetic methods. The total cost of producing onions using IPM methods was more than the total cost using synthetic pesticides. For all three vegetables, the yields on the IPM plots were greater than the yield on the synthetic pesticide plots. All four vegetables in Surkhet cost less to produce using IPM methods and led to greater yield.

Using the economic surplus method, we estimated the market-level benefits from IPM adoption in Banke and Surkhet. Because there is greater tomato, cauliflower, and onion production in Banke, the cumulative benefits were greater than Surkhet. In total, the results predict cumulative IPM benefits of $1.06 to $1.44 million between the two districts.

As IPM adoption in Banke and Surkhet increases, so will aggregate benefits. Therefore, to yield greater benefits, IPM extension and out-reach programs should focus on increasing adoption of complex practices.

6.2 Limitations and Extensions

One variable that may have caused issues in the adoption model was pest severity, a dummy variable where one represented severe pest damage and zero represented little to no pest damage. As pest damage worsens, farmers turn to various methods of pest control. When a farmer chooses to use a control method, pest severity decreases, thus decreasing the need for pest management products. Future research needs to control for endogeneity of severity measures in IPM adoption.

Two limitations of the economic impact study are that: 1) the field trials had small (n =3 or n=4) sample sizes, and 2) most of the yield and cost changes were not statistically significant. If more experimental trials on the costs and benefits of IPM were performed in Nepal in the future, this could provide more precise estimates of yield and cost changes from using IPM practices for Nepali farmers.

Compared to previous cross-sectional surveys in Nepal, our survey showed significantly lower IPM adoption rates, which could have been affected by the ongoing COVID-19 pandemic and resulting economic downturn. While we tried to incorporate some impacts, including access to inputs during the pandemic that could directly influence the adoption process, it is too early to ascertain the full extent that the COVID-19 pandemic has had on farm households and their IPM adoption decisions. Future studies could evaluate COVID-19 effects by extending our analysis and comparing adoption rates in subsequent years to our results.

A specific focus in our analyses was to examine how IPM adoption differs by caste or ethnic group. For cucumber farmers, compared to members of the high-caste group, being in the low-caste group (i.e., Muslim or Dalit) positively affects IPM adoption. However, for cauliflower farmers, we found that compared to the high caste group, there is a negative relationship between belonging to a middle-caste and adoption of complex practices. An objective of future studies could be to determine if an individual's caste negatively influences adoption of new agricultural technologies and if so, explore ideas to overcome adoption constraints associated with caste.

Lastly, since our results signify that gender and IPM training are significant factors affecting complex IPM adoption, future analyses could extend our analysis to understand training impacts further. For example, our survey did not gather qualitative information on the methods of IPM training and training facilitators, which could provide additional insights into which training techniques are most effective at disseminating IPM adoption.

6.3 Concluding Remarks

This study provides information on the extent of IPM practices by Nepali vegetable farmers and adds to the understanding of factors that influence adoption of complex IPM practices. We determined the extent of adoption by comparing adoption of individual practices and determining the differences simple and complex IPM practices. In our analysis of factors affecting adoption of complex IPM practices, our findings indicate that IPM training and gender have a significant influence on complex IPM adoption. Using a surplus approach, we estimated the economic impacts of IPM adoption, which might be of particular interest to programs wishing to link IPM activities to impact.

The majority of Nepal's population relies on agriculture, so invasive and native pests' ability to devastate farmers' crop yields is a significant concern. To protect farm households' food security and livelihoods, it is imperative to find effective pest management products and practices. Integrated pest management is a viable alternative to conventional synthetic pesticides and can lead to important economic benefits for farmers and consumers. In order to yield these benefits and achieve greater widespread adoption, IPM programs should focus on extending IPM training activities and developing gender-responsive dissemination strategies.

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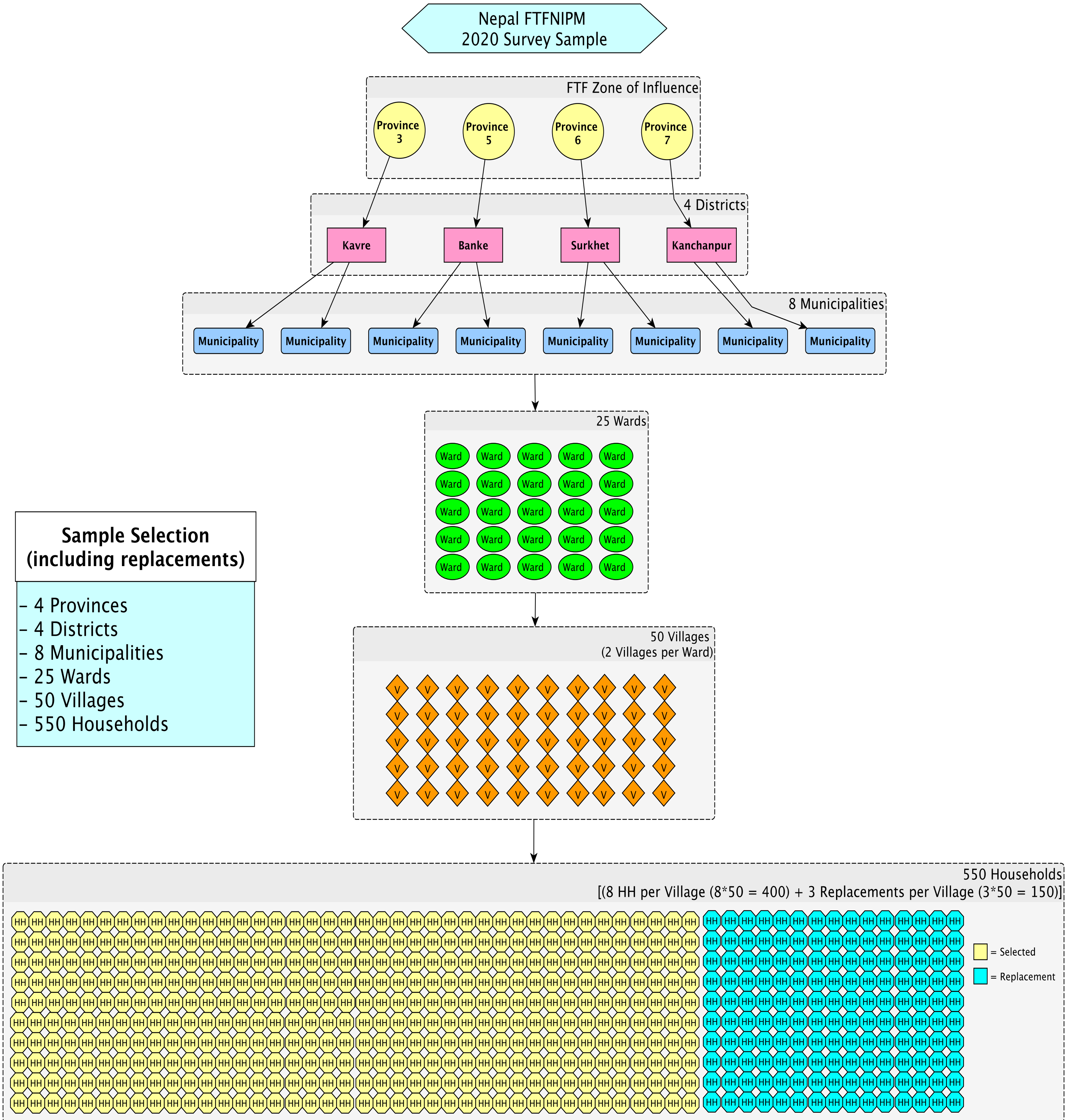
Appendix A: 2021 Survey Sampling Process



Appendix B: Correlation of Adoption Model Variables

B.1 Tomato Variables

Variable	adopt	train	villtr~n	age	labor	migrant	dvet	dexten
adopt	1.00							
train	0.29	1.00						
villtrain	0.18	0.55	1.00					
age	-0.02	0.10	0.01	1.00				
labor	-0.06	-0.04	-0.07	0.01	1.00			
migrant	-0.09	0.03	0.13	-0.05	-0.03	1.00		
dvet	0.10	0.00	-0.06	-0.01	0.04	-0.05	1.00	
dexten	0.06	0.09	0.07	-0.01	-0.07	0.00	0.46	1.00
exp	-0.10	0.07	-0.04	0.49	0.06	0.05	0.03	0.09
land	0.03	0.17	0.03	0.13	0.38	-0.04	-0.02	0.01
memb	0.04	0.02	0.11	0.05	0.04	0.03	-0.08	-0.02
none	-0.16	-0.12	-0.13	0.33	0.05	0.10	0.01	-0.07
primary	-0.02	0.05	0.10	0.09	-0.05	-0.05	0.02	-0.08
secondary	0.01	0.03	0.10	-0.22	0.08	0.03	-0.01	0.07
collegeslc	0.17	0.04	-0.07	-0.22	-0.06	-0.08	-0.02	0.09
severe	-0.15	0.09	-0.03	-0.01	0.17	0.05	0.04	0.00
cbf	0.16	0.29	0.11	-0.04	-0.01	-0.09	0.01	-0.01
input	0.08	-0.14	0.01	0.00	-0.06	-0.08	0.06	-0.17
female	-0.14	-0.05	0.09	-0.38	-0.06	0.18	-0.11	-0.18
district1	0.17	0.21	0.39	0.00	-0.05	0.05	0.27	0.24
district2	-0.12	0.16	0.30	0.13	0.01	0.07	-0.16	-0.02
district3	-0.12	-0.24	-0.48	-0.18	0.19	0.04	0.02	-0.04
district4	0.10	-0.17	-0.30	0.05	-0.17	-0.19	-0.14	-0.21
highcaste	0.09	0.05	0.02	0.02	-0.31	0.08	0.05	0.10
midcaste	-0.05	-0.02	0.06	-0.07	0.30	-0.07	-0.16	-0.13
lowcaste	-0.09	-0.06	-0.17	0.09	0.03	-0.02	0.20	0.06

Variable	exp	land	memb	none	primary	second~y	colleg~c	severe
exp	1.00							
land	0.14	1.00						
memb	-0.08	-0.08	1.00					
none	0.15	-0.10	-0.10	1.00				
primary	0.04	0.02	0.06	-0.37	1.00			
secondary	-0.09	0.06	0.09	-0.30	-0.33	1.00		
collegeslc	-0.10	0.02	-0.04	-0.34	-0.37	-0.30	1.00	

severe	0.05	-0.05	-0.18	0.09	-0.14	0.06	0.00	1.00
cbf	-0.06	-0.01	0.08	-0.20	0.05	0.06	0.09	-0.08
input	-0.14	-0.12	0.09	-0.02	0.10	-0.04	-0.04	-0.01
female	-0.25	-0.23	-0.08	0.22	-0.12	0.00	-0.09	0.17
district1	-0.01	-0.06	0.15	-0.17	0.15	0.05	-0.04	-0.03
district2	0.14	0.26	-0.10	-0.02	-0.01	0.08	-0.05	0.03
district3	0.02	-0.02	-0.18	0.17	-0.15	-0.03	0.01	0.02
district4	-0.18	-0.24	0.15	0.03	-0.01	-0.13	0.09	-0.03
highcaste	-0.07	-0.23	0.17	-0.21	0.03	0.10	0.08	-0.04
midcaste	0.02	0.22	-0.09	0.14	-0.02	-0.09	-0.03	-0.01
lowcaste	0.11	0.04	-0.18	0.15	-0.02	-0.03	-0.10	0.09

Variable	**cbf**	**input**	**female**	**distri~1**	**distri~2**	**distri~3**	**distri~4**	**highca~e**
cbf	1.00							
input	-0.04	1.00						
female	0.00	0.05	1.00					
district1	0.18	-0.04	-0.12	1.00				
district2	-0.06	-0.05	-0.01	-0.42	1.00			
district3	-0.16	-0.09	0.10	-0.33	-0.41	1.00		
district4	0.06	0.22	0.03	-0.26	-0.32	-0.25	1.00	
highcaste	0.11	0.10	0.02	0.13	-0.11	-0.21	0.23	1.00
midcaste	-0.10	-0.10	0.03	-0.11	0.07	0.18	-0.18	-0.88
lowcaste	-0.02	-0.01	-0.09	-0.05	0.08	0.06	-0.11	-0.30

Variable	**midcaste**	**lowcaste**
midcaste	1.00	
lowcaste	-0.19	1.00

Appendix B: Correlation of Adoption Model Variables

B2. Cauliflower Variables

Variable	adopt	train	villtr~n	age	labor	migrant	dvet	dexten
adopt	1.00							
train	0.25	1.00						
villtrain	0.20	0.55	1.00					
age	0.10	0.02	-0.05	1.00				
labor	0.05	-0.05	-0.08	0.05	1.00			
migrant	-0.04	0.02	0.11	-0.07	-0.03	1.00		
dvet	0.05	0.01	-0.08	-0.02	0.07	0.01	1.00	
dexten	0.02	0.07	0.03	-0.05	0.02	-0.05	0.51	1.00
exp	0.05	0.15	0.01	0.44	0.12	0.00	0.05	0.06
land	0.07	0.14	0.02	0.03	0.45	-0.06	0.05	0.06
memb	-0.02	0.02	0.05	0.12	0.00	0.01	-0.11	-0.10
none	-0.02	-0.11	-0.15	0.32	0.12	0.03	0.03	-0.06
primary	0.01	0.01	0.05	0.15	-0.02	-0.05	0.05	-0.04
secondary	-0.10	-0.04	0.09	-0.20	-0.01	0.08	-0.10	-0.02
collegeslc	0.10	0.13	-0.01	-0.24	-0.08	-0.06	0.02	0.12
severe	-0.12	-0.03	-0.11	0.02	0.02	0.09	0.02	0.07
cbf	0.18	0.31	0.08	0.04	-0.04	-0.05	0.02	0.05
input	-0.01	-0.13	0.01	0.07	-0.11	0.01	0.01	-0.12
female	-0.16	0.04	0.14	-0.35	-0.11	0.20	-0.08	-0.15
district1	0.13	0.21	0.36	-0.04	-0.09	0.09	0.20	0.14
district2	0.02	0.25	0.41	0.03	0.11	-0.04	-0.09	0.06
district3	-0.10	-0.31	-0.52	-0.19	0.15	0.02	0.07	-0.06
district4	-0.05	-0.18	-0.30	0.20	-0.18	-0.07	-0.17	-0.16
highcaste	0.05	0.01	0.04	0.08	-0.30	0.07	-0.02	0.10
midcaste	-0.08	0.00	0.03	-0.09	0.28	-0.08	-0.04	-0.13
lowcaste	0.05	-0.01	-0.13	0.02	0.06	0.01	0.11	0.04

Variable	exp	land	memb	none	primary	second~y	colleg~c	severe
exp	1							
land	0.19	1.00						
memb	0.05	-0.06	1.00					
none	0.09	-0.02	-0.10	1.00				
primary	0.10	0.02	0.09	-0.31	1.00			
secondary	-0.06	-0.01	0.04	-0.31	-0.37	1.00		
collegeslc	-0.11	0.00	-0.04	-0.30	-0.36	-0.35	1.00	
severe	0.03	-0.12	-0.10	0.12	-0.11	0.04	-0.04	1.00

cbf	-0.07	0.01	0.07	-0.14	-0.03	-0.02	0.18	-0.06
input	0.03	-0.12	0.15	-0.01	0.05	-0.02	-0.01	-0.02
female	-0.20	-0.12	-0.12	0.20	-0.14	0.02	-0.05	0.17
district1	-0.04	-0.10	0.10	-0.15	0.15	-0.03	0.01	-0.02
district2	0.16	0.25	-0.10	-0.02	-0.05	0.07	0.00	-0.02
district3	-0.06	-0.02	-0.11	0.18	-0.08	-0.05	-0.04	0.16
district4	-0.07	-0.15	0.13	-0.02	-0.01	0.00	0.03	-0.12
highcaste	-0.06	-0.26	0.14	-0.18	-0.04	0.09	0.12	0.01
midcaste	0.02	0.29	-0.11	0.18	0.02	-0.11	-0.08	-0.06
lowcaste	0.08	-0.04	-0.07	0.01	0.04	0.04	-0.09	0.11

Variable	**cbf**	**input**	**female**	**distri~1**	**distri~2**	**distri~3**	**distri~4**	**highca~e**
cbf	1.00							
input	-0.10	1.00						
female	-0.10	0.07	1.00					
district1	0.17	0.01	-0.04	1.00				
district2	-0.01	-0.09	0.03	-0.37	1.00			
district3	-0.17	-0.11	0.11	-0.31	-0.38	1.00		
district4	0.01	0.20	-0.11	-0.29	-0.36	-0.29	1.00	
highcaste	0.08	0.17	-0.04	0.15	-0.23	-0.21	0.31	1.00
midcaste	-0.09	-0.14	0.10	-0.15	0.21	0.16	-0.25	-0.86
lowcaste	0.01	-0.08	-0.10	-0.01	0.04	0.10	-0.14	-0.32

Variable	**midcaste**	**lowcaste**
midcaste	1.00	
lowcaste	-0.20	1.00

Appendix B: Correlation of Adoption Model Variables

B.3 Onion Variables

Variable	adopt	train	villtr~n	age	labor	migrant	dvet	dexten
adopt	1.00							
train	0.31	1.00						
villtrain	0.11	0.58	1.00					
age	0.02	0.00	-0.01	1.00				
labor	0.00	0.04	0.01	0.08	1.00			
migrant	0.06	0.03	0.09	-0.11	-0.03	1.00		
dvet	0.01	-0.02	-0.02	0.00	0.07	0.02	1.00	
dexten	-0.06	0.06	0.05	-0.03	0.03	0.06	0.33	1.00
exp	0.00	0.14	0.03	0.50	0.06	0.02	0.01	0.06
land	-0.02	0.06	0.02	0.08	0.31	-0.05	0.00	0.01
memb	-0.03	0.05	0.15	0.06	0.13	0.04	-0.15	-0.12
none	-0.08	-0.06	-0.06	0.43	0.03	-0.10	0.03	-0.10
primary	0.09	-0.06	-0.03	0.06	-0.06	-0.05	-0.05	-0.16
secondary	-0.03	0.00	0.10	-0.22	0.04	0.08	-0.02	0.04
collegeslc	0.03	0.12	0.00	-0.30	-0.01	0.08	0.04	0.23
severe	-0.05	-0.06	-0.15	0.03	0.05	0.13	0.06	-0.04
cbf	0.15	0.19	0.13	-0.01	0.06	-0.01	0.02	-0.05
input	0.02	-0.11	-0.06	-0.05	-0.03	-0.03	0.15	-0.05
female	-0.10	-0.04	-0.06	-0.39	-0.10	0.16	-0.08	-0.13
district1	-0.05	0.11	0.31	0.02	-0.06	0.02	0.19	0.23
district2	0.02	0.19	0.36	0.02	0.07	0.07	-0.18	0.01
district3	0.02	-0.19	-0.52	-0.14	0.06	0.05	0.04	-0.12
district4	0.01	-0.18	-0.24	0.12	-0.09	-0.19	-0.05	-0.16
highcaste	0.00	0.05	0.11	0.04	-0.24	0.20	0.00	0.13
midcaste	-0.01	-0.05	-0.06	-0.07	0.23	-0.20	-0.08	-0.23
lowcaste	0.03	0.01	-0.09	0.05	0.03	-0.01	0.15	0.16

Variable	exp	land	memb	none	primary	second~y	colleg~c	severe
exp	1.00							
land	0.15	1.00						
memb	-0.03	-0.10	1.00					
none	0.10	-0.04	-0.12	1.00				
primary	0.04	-0.05	0.07	-0.38	1.00			
secondary	-0.04	0.05	0.06	-0.33	-0.32	1.00		

collegeslc	-0.11	0.05	0.01	-0.35	-0.33	-0.29	1.00	
severe	0.03	0.05	-0.12	0.11	-0.04	-0.11	0.03	1.00
cbf	0.01	0.04	0.03	-0.07	-0.09	0.10	0.08	-0.18
input	-0.08	-0.05	0.15	-0.08	0.12	-0.08	0.04	-0.07
female	-0.24	-0.19	-0.07	0.12	-0.07	0.05	-0.11	-0.06
district1	0.00	-0.11	0.12	-0.16	0.15	0.05	-0.03	-0.06
district2	0.12	0.23	-0.03	-0.02	-0.14	0.18	-0.02	-0.21
district3	-0.03	-0.03	-0.17	0.14	-0.06	-0.12	0.04	0.21
district4	-0.12	-0.14	0.10	0.05	0.07	-0.16	0.02	0.10
highcaste	-0.05	-0.22	0.14	-0.25	0.11	0.06	0.09	-0.04
midcaste	0.04	0.28	-0.07	0.20	-0.08	-0.07	-0.06	-0.04
lowcaste	0.04	-0.09	-0.14	0.11	-0.07	0.01	-0.05	0.15

Variable	**cbf**	**input**	**female**	**distri~1**	**distri~2**	**distri~3**	**distri~4**	**highca~e**
cbf	1.00							
input	0.03	1.00						
female	0.10	0.12	1.00					
district1	0.03	0.04	-0.03	1.00				
district2	0.05	-0.15	-0.03	-0.45	1.00			
district3	-0.16	-0.03	0.16	-0.37	-0.41	1.00		
district4	0.09	0.20	-0.13	-0.24	-0.27	-0.22	1.00	
highcaste	0.10	0.17	0.03	0.20	-0.07	-0.29	0.21	1.00
midcaste	-0.05	-0.14	-0.01	-0.29	0.13	0.29	-0.16	-0.86
lowcaste	-0.11	-0.08	-0.04	0.16	-0.11	0.04	-0.10	-0.34

Variable	**midcaste**	**lowcaste**
midcaste	1	
lowcaste	-0.20	1.00

Appendix B: Correlation of Adoption Model Variables

B.4 Cucumber Variables

Variable	adopt	train	villtr~n	age	labor	migrant	dvet	dexten
adopt	1.00							
train	0.37	1.00						
villtrain	0.20	0.54	1.00					
age	0.00	0.07	0.00	1.00				
labor	0.06	0.07	0.00	0.02	1.00			
migrant	0.03	-0.04	0.06	0.03	0.01	1.00		
dvet	0.20	0.13	0.04	-0.05	0.11	0.02	1.00	
dexten	0.10	0.15	0.08	-0.12	0.00	-0.11	0.55	1.00
exp	0.11	0.15	-0.04	0.44	0.08	0.17	0.06	0.03
land	0.13	0.14	0.02	0.06	0.37	0.01	0.04	0.05
memb	0.11	0.03	0.13	0.11	0.05	-0.10	0.07	0.04
none	-0.16	-0.12	-0.16	0.30	0.07	0.08	0.00	-0.15
primary	0.05	0.03	0.06	0.10	-0.02	-0.08	0.06	-0.06
secondary	-0.03	0.00	0.11	-0.13	-0.05	0.04	0.01	0.07
collegeslc	0.14	0.09	-0.01	-0.28	-0.01	-0.04	-0.07	0.14
severe	-0.11	-0.06	-0.18	-0.04	0.04	0.07	0.03	0.11
cbf	0.25	0.35	0.16	0.04	0.00	-0.09	0.02	0.04
input	-0.02	-0.14	-0.01	0.09	-0.16	-0.11	-0.01	-0.14
female	-0.21	-0.07	0.06	-0.36	-0.12	0.16	-0.04	-0.21
district1	0.06	0.29	0.48	-0.10	-0.01	0.00	0.24	0.19
district2	0.12	0.31	0.44	0.07	0.10	0.04	-0.09	0.06
district3	-0.20	-0.30	-0.53	-0.17	0.12	0.13	0.08	-0.05
district4	0.04	-0.25	-0.32	0.20	-0.20	-0.16	-0.21	-0.18
highcaste	0.02	-0.03	0.07	0.05	-0.37	0.04	0.07	0.12
midcaste	-0.05	0.04	0.00	-0.06	0.33	-0.12	-0.06	-0.13
lowcaste	0.05	0.00	-0.12	0.01	0.09	0.15	-0.03	0.01
Variable	**exp**	**land**	**memb**	**none**	**primary**	**second~y**	**colleg~c**	**severe**
exp	1.00							
land	0.17	1.00						
memb	0.02	-0.05	1.00					
none	0.12	0.01	-0.17	1.00				
primary	0.08	0.02	0.15	-0.34	1.00			
secondary	-0.09	-0.02	0.02	-0.32	-0.33	1.00		
collegeslc	-0.11	-0.02	0.00	-0.34	-0.34	-0.32	1.00	
severe	0.12	-0.02	-0.25	0.07	-0.05	0.02	-0.04	1.00

cbf	-0.06	0.04	0.10	-0.09	-0.03	-0.01	0.14	-0.26
input	-0.04	-0.03	0.07	-0.01	0.06	-0.04	-0.01	-0.10
female	-0.12	-0.18	-0.15	0.24	-0.11	-0.06	-0.07	-0.05
district1	-0.12	-0.06	0.15	-0.21	0.09	0.12	0.00	-0.04
district2	0.13	0.21	-0.07	0.04	0.00	0.03	-0.06	-0.18
district3	0.09	0.05	-0.25	0.21	-0.08	-0.08	-0.05	0.23
district4	-0.11	-0.19	0.17	-0.05	0.00	-0.05	0.10	-0.03
highcaste	-0.11	-0.29	0.19	-0.28	0.00	0.17	0.12	-0.07
midcaste	0.12	0.34	-0.10	0.24	0.03	-0.24	-0.04	-0.05
lowcaste	-0.01	-0.06	-0.19	0.10	-0.06	0.11	-0.16	0.21
Variable	**cbf**	**input**	**female**	**distri~1**	**distri~2**	**distri~3**	**distri~4**	**highca~e**
cbf	1.00							
input	-0.05	1.00						
female	-0.03	0.05	1.00					
district1	0.11	-0.14	-0.01	1.00				
district2	0.18	-0.06	-0.04	-0.28	1.00			
district3	-0.25	-0.07	0.21	-0.33	-0.33	1.00		
district4	-0.03	0.25	-0.17	-0.33	-0.33	-0.39	1.00	
highcaste	0.05	0.21	-0.10	0.17	-0.30	-0.30	0.42	1.00
midcaste	-0.04	-0.14	0.13	-0.16	0.25	0.27	-0.35	-0.86
lowcaste	-0.02	-0.16	-0.04	-0.03	0.13	0.08	-0.17	-0.34
Variable	**midcaste**	**lowcaste**						
midcaste	1.00							
lowcaste	-0.18	1.00						