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Human Dimensions of Natural Resources: A Case of Farmers in Northern Rwanda

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Human Dimensions of Natural Resources: A Case of Farmers in Northern Rwanda

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Degree
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DEDICATION

I dedicate this work to my wife whose patience and love sustained me; my late parents who would have been proud; and my family and friends who helped me throughout the process.

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ABSTRACT

As food demand increases globally, the world faces the challenge of feeding everyone without harming the environment. Meeting this challenge requires increased food production. Paradoxically, increased food production can harm the environment and natural resources. Change in consumption patterns offers an opportunity to reconcile the increase in food production and environmental protection. However, consumption patterns can only change if they are perceived first, then acted upon. Research shows that people who perceive their consumption of natural resources are more likely to conserve them as they can see how much they are consuming. This study investigated perceptions of natural resources and environmental behaviors among farmers in Musanze District, northern Rwanda. The first part of this research investigated perceptions of water and charcoal consumption among farmers. A survey was used to collect data from 323 farmers involved in a poultry development project in the district. Results indicate that the perception of charcoal consumption was associated with three variables: living in the urban section of the district, the amount of feed consumed by chickens, and the elevation at which the coop is located. To examine farmers' environmental behaviors, the second chapter of the research employed the various existing theories to assess the influence of attitudes, subjective norms, perceived behavior control, and other factors on farmers' behavioral intent to engage in rainwater harvesting, the use of organic fertilizer, and the use of alternative sources of energy for domestic cooking. To conduct the study, a survey was conducted from a randomly selected sample of 604 farmers from 7 sectors of the district of Musanze in northern Rwanda. A Structural Equation Model (SEM) approach was used to analyze data. Results revealed that farmers' decision to engage in environmental behaviors depends on their attitudes, social norms, perceived behavior control, and other background factors. Overall, the results provided useful insights into understanding farmers' decision-making towards nature and the environment. The last part of the research applied spatial analysis to examine farmers' behaviors. Results showed that in addition to the presence of spatial dependence, there are spatial clusters of farmers' behavioral intent in some regions of the study area.

Keywords: Perceptions, Behaviors, Natural resources, Farmers, Rwanda

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INTRODUCTION

Perceptions and Natural Resources

The scarcity of natural resources continues to be a challenge in Rwanda. Concerning water, projections indicate a further increase in water demand, despite the laudable steps Rwanda has taken to improve water supply and access (MININFRA, 2013; UNEP, 2010). The projected increase in water demand result from factors such as population growth, urbanization, rapid economic development, and decreasing mortality rate (MINIRENA, 2012), agricultural intensification and industrialization (NISR, 2019). Similar to water, energy resources constitute an additional challenge as rural households in Rwanda rely on biomass consumption (i.e. charcoal and firewood), mainly for cooking. Slander and Hendriksen (2012) reported that as of 2011, approximately 86% of primary energy in Rwanda came from biomass, mainly in the form of wood. In Rwanda, the use of charcoal in rural areas is likely to increase due to continued urbanization and an increasing population (Marge, 2009). Given the adverse effects of biomass dependence on the environment particularly forest resources (Bimenyimana, Asemota, & Li, 2018; Mazimpaka, 2014), one of the challenges facing Rwanda's energy sector is to produce and consume biomass-based energy without harming the environment (Munyaneza et al., 2016). In the face of increasing demand for both water and charcoal, understanding farmers' perceptions of these resources and their consumption are important. Research indicates that people who understand their resource consumption patterns may be more likely to conserve them (Fan et al., 2014; Kuil et al., 2018). To date, farmers' perceptions of both water and charcoal consumption in Rwanda is not documented in literature. We are unlikely to make sound policies to improve farmers' decision-making and ultimately their behaviors if we do not understand farmers' perceptions of natural resource consumption.

Behaviors and Natural Resources

The first chapter in this study investigated the perceptions of natural resource consumption and the factors that affect those perceptions. The growing population and the soaring demand for animal-sourced foods continue to drive the increasing demand for food globally (Alexandratos & Bruinsma, 2012; World Resources Institute, 2018). While increased food production may offer a solution FAO (2009), it may also likely place further pressure on natural resources (Alexandratos & Bruinsma, 2012) and can lead to environmental degradation (Donohoe, 2003). The challenge, then, is how to feed the world while preserving the environment. Meeting the challenge of sustainably feeding the world can depend on people's choices and behaviors. Choices such as food consumption can have a considerable impact on the environment (Leach et al., 2012). For example, by eliminating certain behaviors (e.g., maintaining our high demand for high-calorie animal-based diets; high volumes of food waste and loss; among others), the global society could balance food production and protection of the environment (McLaughlin & Kinzelbach, 2008). However, some practices are not easy to eliminate. For example, it is unlikely that people will be willing to give up meat consumption despite the benefit of that behavior on natural resources (Odegard & van der Voet, 2014). The complex relationship between behaviors, food consumption, and natural resources highlights the importance of a better understanding of environmental behaviors in the context of agricultural production and food consumption. The primary goal of the second article of this research was to investigate environmental behaviors and their determinants among farmers in Rwanda. The results of this research will contribute to the current literature by employing an integrated framework in modeling farmers' environmental behaviors based on existing theories: The Theory of Planned Behavior, the Socio-Cognitive Theory, and the Reasoned Action Approach. More specifically, the results from the study will provide a better understanding of how psychological and socio-economic factors (as background factors) play an important role in shaping farmers' behavioral intent to engage in environmental behaviors. Lastly, the results of the study will provide policy options for adopting more environmentally friendly behaviors among farmers.

Spatial analysis of environmental behaviors

Research shows that people may behave in a certain way because of their spatial proximity to other people or the physical environment – this concept is sometimes referred to as local norms (Fornara et al., 2011). This notion has been applied to study environmental behaviors. For example, Passafaro et al. (2019) investigated local norms to understand the effects of spatial proximity on recycling intentions and self-reported behavior. Their findings indicate that spatial proximity directly influenced recycling behavior, and concluded that neighbors' influence to recycle waste is important in shaping the intention to behave. Additionally, residential proximity can also determine behavior; i.e., residents of a given area may behave differently than non-resident of that area (Yoon et al., 2010). Agovino et al. (2016) found that waste collection behavior tended to be strongly influenced by proximity; provinces with good levels of environmental pro-sociality were found to positively influence nearby ones. Similarly, Garekae et al. (2016) studied attitudes of local communities towards forest conservation in Botswana and found that community members in one village held stronger conservation attitudes towards a forest reserve than those living in the other two villages. Authors ascribe the strong attitudes towards forest coservation to education and prior engagement in conservation efforts. The influence of proximity is derived from the idea that things that are close to each other are more similar than things that are farther apart, an idea that is expressed as the first law of geography (Tobler, 1979). This study argues that this spatial proximity is relevant in explaining farmers' behavioral intent. To date, however, no studies have conducted spatial analysis of environmental behaviors in Rwanda or Musanze district in particular. The third article of this research primarily examined the spatial patterns of behavioral intent to harvest rainwater, use organic fertilizer, use alternative sources of energy for domestic cooking among farmers in Musanze district.

CHAPTER I
PERCEPTIONS OF NATURAL RESOURCES USE IN RWANDA – A PARTIAL PROPORTIONAL ODDS MODEL

A version of this chapter was originally published by Jean François Régis Nisengwe, Adam Willcox (Ph.D.), Liem Tran (Ph.D.):

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The following article was submitted and published as a result of collaboration between the student and two co-authors. The student conducted the literature review, performed data analysis, wrote the manuscript draft, and led the submission process to the reviewers of the journal. The draft of the manuscript was revised by the co-authors before submission. Adam Willcox Ph.D. provided guidance and assistance in preparing the questionnaire and the theoretical background for the study. Liem Tran Ph.D. offered technical and statistical assistance in analyzing data and revising the manuscript before submission.

Abstract

The scarcity of natural resources constitutes a challenge in Rwanda. Although Rwanda has improved water supplies, projections show a further increase in water demand. Particularly, agriculture continues to place further demands on water resources through intensification and industrialization. Similarly, although the dependence on biomass for cooking has improved over the past two decades in Rwanda, the ratio is still high and is projected to increase. Unfortunately, the heavy dependence on biomass is damaging to the environment in general, and forests in particular. As the consumption of water and charcoal increases, it will be important to study how people perceive their consumption. Research shows that people who perceive their consumption of natural resources are more likely to conserve them as they can see how much they are consuming. This study investigated perceptions of water and charcoal consumption among farmers in northern Rwanda. A survey was used to collect data from 323 farmers involved in a poultry development project in the district of Musanze, northern Rwanda. A Partial Proportional Odds Model (PPOM) was used to analyze the effect of different factors on the perception of natural resource consumption. Results indicate that the perception of charcoal consumption was associated with three variables: living in the urban section of the district, the amount of feed consumed by chicken, and elevation at which the coop is located. One recommendation is that food security projects should consider incorporating farmers' perceptions of their natural resource consumption and put in place mechanisms to track actual natural resource consumption.

Keywords: Perceptions, natural resource consumption, charcoal, water, Rwanda, Partial Proportional Odds Model

Introduction

Background of the study

The scarcity of natural resources continues to be a challenge in Rwanda. Concerning water, the literature indicates that by 2010, daily per capita consumption of water was around 13 liters per day in Rwanda; this quantity is lower than the envisaged standard consumption of 20 liters (MININFRA, 2013). According to the World Health Organization (WHO, 2013), 20 liters per capita is the quantity needed to take care of basic hygiene needs and basic food hygiene. Rwanda is lagging behind because of the scarcity of water resources. More recently, Nkurunziza (2016) reported that the average water consumption per capita in the northern part of Rwanda is estimated to be between 4.7 and 12.3 liters per day. Additionally, the study reported that 21.58% of respondents fetched water more than 1000 meters from their residence and that 38.91% of respondents took more than 30 minutes to collect water. Although Rwanda has taken laudable steps to improve water supply and access, projections continue to show a further increase in water demand (MININFRA, 2013; UNEP, 2010). The projected increase in water demand is based on factors such as population growth, urbanization, rapid economic development, and decreasing mortality rate (MINIRENA, 2012). Additionally, agriculture continues to place further demands on water resources, particularly, intensification and industrialization (NISR, 2019). Agriculture consumes more water than any other sector in Rwanda (over 65%) (Bizuhoraho et al., 2018). Although much of water consumption in agriculture comes from irrigation activities, data suggest that livestock development, especially cattle, consumes water resources to an appreciable degree (MINIRENA, 2012).

Similar to water, energy resources are an additional challenge as rural households in Rwanda rely on biomass consumption (i.e. charcoal and firewood), mainly for cooking. Slander and Hendriksen (2012) reported that as of 2011, approximately 86% of primary energy in Rwanda came from biomass, mainly in the form of wood; wood is either used directly as fuel (57%) or converted into charcoal (23%) together with smaller amounts of crop residues and peat (6%). Although the dependence on biomass has improved over the past two decades (from 95% to 86%), the ratio is still high (Bimenyimana et al., 2018). In Rwanda, the use of charcoal in rural areas is likely to increase due to continued urbanization and an increasing population (Marge, 2009). Specifically, one of the challenges facing Rwanda's energy sector is to produce and consume biomass-based energy without harming the environment (Munyaneza et al., 2016). Unfortunately, the heavy dependence on biomass is intrinsically damaging to the environment in general, particularly forest resources (Bimenyimana et al., 2018; Mazimpaka, 2014).

As the demand for both water and charcoal continues to increase, understanding farmers' perceptions of these resources and their consumption are important. Research is starting to indicate that people who accurately understand their resource consumption patterns may be more likely to conserve them since they are aware of how much they are consuming as they can personally assess how changes in their behavior affect resource consumption. For example, in a study done by Fan et al. (2014) in the Wei River Basin in China, it was reported that household water consumption can be easily reduced when people understand their consumption. A good understanding of farmers' perception of water availability and use is crucial as perception can affect their decisions and behaviors such as crop choice and water allocation (Kuil et al., 2018). To date, there exist no resources in the literature that show farmers' perceptions of both water and charcoal consumption in Rwanda. Until we understand farmers' perceptions of natural resource consumption, we cannot make sound policies to improve farmers' decision-making and ultimately their behaviors. Nor can we improve outreach and education programs that are likely to lead to more sustainable consumption patterns of natural resources.

This study investigated the factors that affect the perception of natural resource consumption among farmers in Musanze district, northern Rwanda. To achieve this, the study attempts to answer the following question: What factors influence perceptions of water and charcoal consumption among farmers in Musanze district, northern Rwanda? To answer this question, data were collected from poultry farmers who were taking part in the food security project: *Tworore Inkoko, Twunguke* (TI) – Kinyarwanda for *Let's raise chicken and make a profit*. This project leverages public-private partnerships among USAID/Rwanda; a US-based foundation, African Sustainable Agriculture Project (ASAP); a Rwandan animal feed company, Zamura Feeds Ltd.; and a US land-grant institution, University of Tennessee Institute of Agriculture (UTIA). As part of the project, enrolled farmers receive 100 chicks per six-week cycle and are encouraged to keep at least three of the chickens for consumption at the end of each production cycle. Additionally, the project offers training and support to farmers so they can be successful in their broiler chicken production. The enrolled farmers use charcoal as a source of fuel for chicken brooding and use water to tend to chickens.

Conceptual framework

The decision of farmers to use and manage natural resources can depend on their perception of the resources (Assefa & Hans-Rudolf, 2016). This study argues that people's perceptions about natural resource consumption exert an influence on their attitudes towards natural resources, and ultimately their behavior. Thus, the conceptual framework in this study builds from theories and studies linking behavior and environmental protection (e.gs., Homburg & Stolberg, 2006; Kollmuss & Agyeman, 2002; Levitt, 2013; Sawitri et al., 2015b).

Since farmers' perceptions can vary because of various factors, it is crucial to understand various factors that influence farmers' perceptions of natural resources (Fentie et al., 2013). Several factors can influence the way people perceive natural resources, which, in turn, has implications for the way they manage natural resources. By understanding the factors that influence farmers' perceptions, we can develop better programs that are likely to change farmers' attitudes, and ultimately incentivize them to manage natural resources well. Other studies have taken this approach to investigate farmers' perceptions of natural resources. For example, Ntuli et al. (2019) applied a similar approach to investigate the factors that influence people's perceptions of the conservation of wildlife resources in South Africa. Moges and Taye (2017) also made the same assumptions while studying the determinants of farmers' perceptions to invest in soil and water conservation technologies in Ethiopia. Similarly, Melak et al. (2021) used the same conceptual tenet to investigate the determinants of farmers' perceptions of forest conservation.

Though recognizing the importance of the full behavior-environment conceptual framework, this study focuses only on investigating the perceptions of natural resources and the factors that influence those perceptions. In particular, this study strives to examine the determinants of farmers' perception of charcoal and water resources in the district of Musanze, northern Rwanda (see Figure 1-1).

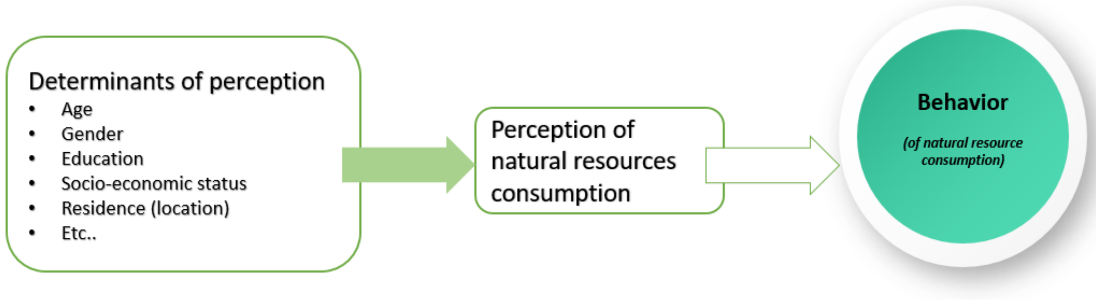

Figure 1-1: Conceptual framework of farmers' perception of natural resource consumption

Materials and Methods

Study area and data

To investigate the factors that affect farmers' perceptions of natural resource use, we surveyed farmers between September and December 2019. With the Institutional Review Board (IRB) approval (IRB number: UTK IRB-17-03708-XM), we collected data from poultry farmers living in Musanze district, northern Rwanda. Musanze district has three sub-levels of administrative units, in order of largest to smallest: Sectors, Cells, and Villages. In this research, we collected data from three sectors where the TI project was running: Kinigi, Muhoza, Gataraga (Figure 1-2). Kinigi and Gataraga sectors are rural sectors while Muhoza is considered an urban/peri-urban sector.

We used a three-stage random sampling approach by administrative unit (cell, village, household). The number of surveys was chosen to be proportional to the larger administrative unit's population. Thus, the survey responses were proportional to the actual populations within each administrative unit to allow for the greatest possibility of accurate representation. This design was inspired by the TI project data collection design for farmers' recruitment, household survey, and project evaluation. Ultimately, 323 farmers were selected.

Data were collected as part of the monitoring and evaluation data collection that the TI project conducts every year[1]. Since the questions on perceptions were asked for the first time, it was safe to assume that there was no response bias on the perception questions. A questionnaire was used to collect data and was administered using tablets. To ensure the quality of the collected data, enumerators were trained by teams from the University of Tennessee Institute of Agriculture (UTIA) and the TI project before the survey. The questionnaire was first tested during a pilot test to minimize errors and biases that could result from the way the questionnaire was designed. The survey was piloted 15 times, with nine females and six males. The pilot was useful in improving the questionnaire; for example, the questions on Food Insecurity Experience Scale (FIES) were reduced from 8 to 6 based on the context in Rwanda.

The instrument was short enough to not be a burden on the interviewee and to allow the enumerators to conduct multiple interviews in a day. The maximum length of time for one respondent to complete the survey was between 10 and 15 minutes.

[1] Data were collected as part of an ongoing project. Thus, it was not possible to gather data on actual consumption behaviors as the project did not track farmers' actual consumption of natural resources. The closest approximation was to get insights from farmers' perception of their resource consumption.

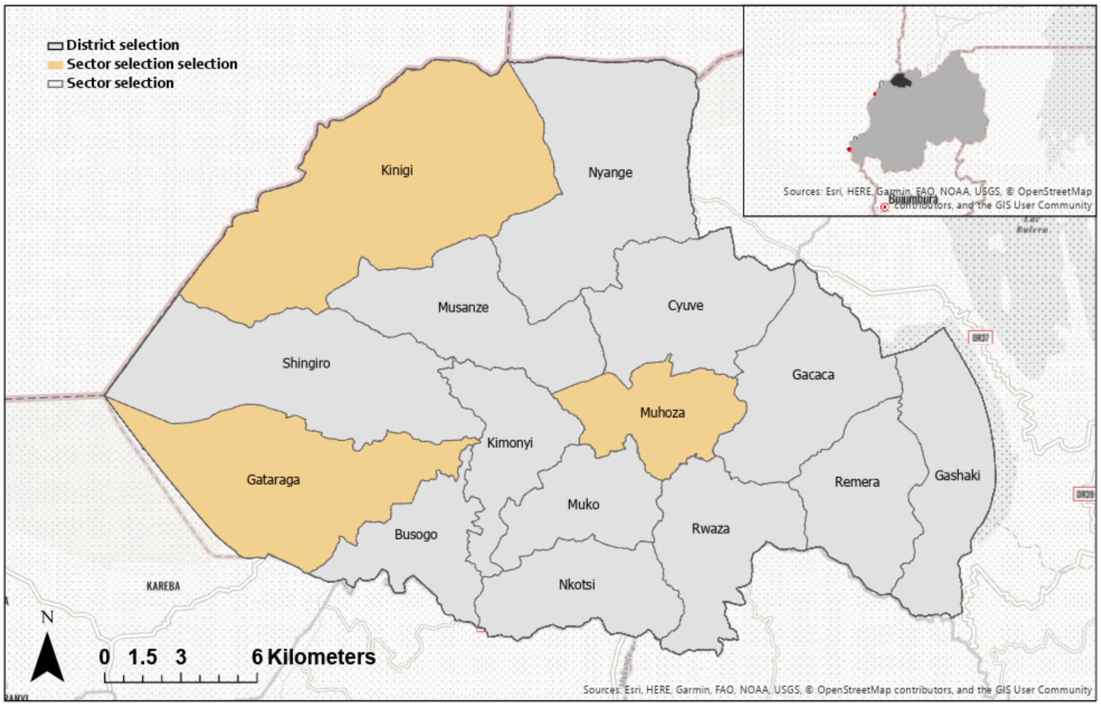

Figure 1-2: Study area (Musanze district, northern Rwanda)

The dependent variables in the study were the perception of water use and perception of charcoal use. Independent variables in the study were age, gender, urban, food insecurity index (FIES)[2], education, feed consumed, and elevation, and ubudehe (a socio-economic status variable). There are four categories of Ubudehe in Rwanda, ranging from 1 to 4. Category 1 includes families who do not own a house and can hardly afford basic needs. Category 2 includes households that have a dwelling of their own or can rent one but rarely get full-time jobs. Category 3 includes households who have a job and farmers who go beyond subsistence farming to produce a surplus that can be sold. The latter also includes those with small and medium enterprises who can employ dozens of people. Category 4 includes those who own large-scale businesses, individuals working with international organizations and industries as well as public servants (GoR, 2015).

Data on elevation was calculated based on the geographical coordinates of every farmer while data on the feed consumed was based on the reported data from the TI project data report. The Food Insecurity Experience Scale (FIES) was adopted from the TI project measure of food security. This measure was also based on the scale developed by (Ballard & Cafiero, 2013). This scale has 8 questions but has been updated by the TI project to have 6 questions from 0 (food secure) to 6 (food insecure).

Data analysis, model specification, and estimation procedures

Proportional Odds Model (POM)

In the context of the study, perception is assessed by evaluating whether farmers feel that their use or consumption of natural resources has changed since they joined the project and to what extent they feel that their resource use has changed. The following measures were used to assess the perception of water consumption: *Our household uses much less water than it did before the project* (Y=1); *Our household uses less water than it did before the project* (Y=2); *Our household uses the same amount of water as it did before the project* (Y=3); *Our household uses more water than it did before the project* (Y=4), and *Our household uses much more water than it did before the project* (Y=5). Similarly, the same measure has been used for the perception of charcoal use: *Our household uses much less charcoal than it did before the project (Y=1); Our household uses less charcoal than it did before the project (Y=2); Our household uses the same amount of charcoal as it did before the project (Y=3); Our household uses more charcoal than it did before the project (Y=4); Our household uses much more charcoal than it did before the project (Y=5)*. These five outcomes constituted the 5-category dependent variable, Y and the number of perception levels (denoted as J in this study) is 5. When a response variable is categorical and ordered, the ordinal logistic regression is the most appropriate model (Anderson, 1984).

One of the commonly used ordinal models is the proportional odds model (POM) (Dolgun & Saracbasi, 2014). The proportional odds model can be intuitively thought of as being based on odds ratios formed over a series of successive incremental cut-points. Each cut-point-

[2] The Food Insecurity Experience Scale by Food and Agriculture Organization (FAO). While the original scale of the index uses 8 questions related to food insecurity, the current study used a modified-scale of 6 questions. The higher the number the more food insecure.

specific estimate is calculated using all observations in the sample, but at a different dichotomization of the outcome (Scott et al., 1997).

The common assumption in an ordinal logistic regression is that the relationship between each pair of outcome groups is the same. Thus, for each independent variable, its effect on the probability of being at or beyond any category is assumed to be the same within the model; thus, the slope estimate provides a summary of each independent variable's relationship to the outcome across all cut-points. This constraint is known as the proportional odds assumption or the parallel regression assumption (O'Connell & Liu, 2011). Thus, ordinal logistic regression assumes that the coefficients that describe the relationship between the lowest level of natural resource perception (Y=1) versus all higher levels of perceptions (Y=2,3,4, and 5) are the same as those that describe the relationship between the next lowest level of natural resource perception (Y=2) and all higher levels (Y=3,4, and 5), etc.

The perception measure Yi can be estimated as follows:

$$Y_i = X_i\beta + \varepsilon \qquad (1)$$

where β is the regression coefficient for X, ε is the identically and independently distributed error term.

Let m_k be the thresholds (cutoffs) for natural resource perception (water or charcoal), k = 1,2,…,J − 1. Note that level k = 1 represents the minimum threshold, *much less water or charcoal*. The different values of Y are as follows:

Y = 1 (much less water or charcoal): if Y ≤ m_1
Y = 2 (less water or charcoal): if m_1 ≤ Y ≤ m_2
Y = 3 (same amount): if m_2 ≤ Y ≤ m_3
Y = 4 (more water or charcoal) if m_3 ≤ Y ≤ m_4
Y = 5 (much more water or charcoal): if Y > m_4

Since J is the number of perception levels, then the probability of perception level (j) for a given variable (i) can be written as:

$$P(Y_i > j) = P_{ij} = \frac{e^{(\alpha_j + X_i\beta)}}{1 + e^{(\alpha_j + X_i\beta)}} \qquad (2)$$

where β is the regression coefficients for X (difference in the log odds of having perception level j vs. other j − 1 perception levels), j is the intercept for j^{th} logit. It is to be noted that the values of the coefficients for all J perception levels will be the same because of the proportional odds assumption. However, this assumption could be violated in many cases. For example, if we consider natural resource perception, ordered logit models assume that the independent variables have the same effect on the occurrence of much less, less, same, more, and much more water or charcoal, thereby resulting in only one set of coefficients for all the influential factors. For the analysis of the perception of natural resource consumption, it is unclear whether the distances between different perception levels are equal or not.

When running any of the ordinal logistic regression models, it is recommended to check whether the assumption of proportionality is satisfied by each independent variable. To check the proportionality assumption, a Likelihood ratio (LR) test can be performed. However, the limitation of the LR test is that it is an omnibus test; as such, it does not show whether the proportionality assumption is violated for all independent variables or only for some (Dolgun &

Saracbasi, 2014). Consequently, a valid method to test the proportionality assumption both in an omnibus and individual manner is preferred.

Brant's Wald test statistic has been proposed to check the proportional odds assumption for all independent variables or only for some (Brant, 1990). The current study used the Brant test to check the proportionality assumption. For example, results from the Brant test conducted on the perception of charcoal consumption (Table 1-3 in appendix) showed that the model violated the proportionality assumption overall (Omnibus) and one variable in particular (FIES). Both the proportional odds model and the Brant test were run using the *MASS* framework by Venables & Ripley (2002) in the R software (R Core Team, 2013).

Partial Proportional Odds Model (PPOM)

The results from the proportional odds model are valid only when the proportionality assumption holds. To test the validity of the model, the Brant test was run on the results from the model, and the test results revealed that the proportionality assumption was violated. When the proportionality assumption holds, one can move forward with the proportional odds model. Conversely, when the test reveals that the assumption does not hold, two options are possible: non-proportional odds model (NPOM) and partial proportional odds model (PPOM). Both models relax the constraints of the proportional odds assumption by allowing all the coefficients to vary in the case of NPOM or allowing some coefficients to vary in the case of PPOM (Dolgun & Saracbasi, 2014; O'Connell & Liu, 2011).

Since our model revealed that not all variables violated the assumption (Table 1-3), the partial proportional odds model seemed to be more appropriate. The partial proportional odds model considers the ordinal nature of the dependent variable while at the same time allowing for possible violation of the proportional odds assumption from explanatory variables (Soon, 2010).

According to the partial proportional odds model, the probability of perception level (j) for a given variable (i) can be written as:

$$P(Y_i > j) = P_{ij} = \frac{e^{(\alpha_j + X_i\beta_j)}}{1 + e^{(\alpha_j + X_i\beta_j)}} \qquad (3)$$

In the PPOM model shown in Eq **Error! Reference source not found.**, when variables (e.g., X_1 and X_2) satisfy the proportional odds assumption, the coefficients for X_1 and X_2 are the same for all levels of the dependent variable. On the other hand, some other variables such as X_3 may not meet the proportional odds assumption, and hence coefficients for X_3 (β_{3j}) are free to vary for different levels of the dependent variable. This scenario can be written as (Sasidharan & Menéndez, 2014):

$$P_{ij} = \frac{e^{(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_{3j})}}{1 + e^{(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_{3j})}} \qquad (4)$$

In the case of our data, this model allowed the perception of natural resources as the dependent variable while allowing the violation of the proportional odds from specific explanatory variables. Failing to relax the model like this can result in incorrect models and results (Ananth & Kleinbaum, 1997). The vector generalized linear and additive model

(VGLM/VGAM) framework within the R software, developed by Yee (2010), was used to address this problem by fitting the data using the partial proportional odds model.

Results

Descriptive statistics

On average, respondents perceive that their consumption of charcoal has increased since the project started (mean = 3.6 and SD = 0.9, on a point scale of 1 to 5). Additionally, results indicate that on average respondents perceive their water consumption has increased (mean = 4.27; SD = 0.59 on a point scale of 1 to 5.

Results (Table 1-4 in appendix) indicate that the majority of respondents (64%) reported that they perceive that they are using more water than before the project started. Less than 2% of respondents feel that the amount of water they use has decreased. Comparatively, only 3% of respondents, feel that the amount of water did not change.

Regarding charcoal, the majority of respondents (66%) perceive that they are using more charcoal than before the project. Conversely, 16% of respondents feel that they are using less charcoal than before the project whereas less than 2% feel that they using even much less charcoal. Comparatively, only 4% of respondents feel that they are using the same amount of charcoal as before the project.

Overall, the mean age for respondents was 40 years (SD = 11). Among all respondents, 50 percent were women. On average, respondents are in category 2 of socioeconomic status (ubudehe). Category 2 represents those who have a dwelling of their own or can rent one but rarely get full-time jobs. The average food insecurity index (FIES) is 2.45. The higher the index the more food insecure the respondent. The highest degree of education attained was university while the mean elevation for all respondents was 2,136 meters (SD = 242). On average, 596.15 kgs of feed was consumed by chickens (SD=160). There are differences in the values across the three sectors (see Table 1-5 in appendix). For example, chickens in Gataraga consume more feed (652.21 kgs/cycle) than chickens in other sectors. Muhoza sector is at the lowest elevation compared to other sectors.

Factors influencing the perception of charcoal consumption

Proportional Odds Model (POM) Results*:* Results show that three variables are associated with the perception of charcoal consumption: *urban*, *feed_consumed*, and *elevation*. According to the results (Table 1-6 in the appendix), farmers who live in the urban section of the district are more likely to feel that their consumption of charcoal has increased since the project started. Regarding *feed_consumed*, results reveal that farmers whose chickens consume more quantity of feed tend to perceive that they use higher quantities of charcoal than before the project started. Lastly, for *elevation*, farmers who live at higher altitudes are more likely to perceive that they are using larger quantities of charcoal than before the project started.

Mathematically, the intercept 1|2 corresponds to logit[$P(Y \leq 1)$]. It can be interpreted as the log of odds of perceiving that one is using 'Much less charcoal' versus perceiving that one is using 'Less charcoal'. Similarly, the intercept 2|3 corresponds to logit[$P(Y \leq 2)$]. It can be interpreted as the log of odds of perceiving that one is using 'Less charcoal' versus perceiving that one is using 'The same amount'. Other intercepts follow the same logic.

Partial Proportional Odds Model: With the partial proportional odds model, the effects of the variables that meet the proportionality assumption are interpreted the same way as in the proportional odds model. For other variables, examining the pattern of coefficients reveals insights that would otherwise be difficult to detect in the case of the proportional odds model (Williams, 2006). In contrast, effects on variables that were allowed to vary (*urban*, *feed_consumed*, and *elevation*) will be interpreted a little differently.

As was the case with the proportional odds model, the results from the partial proportional odds model (Table 1-1) revealed that the three statistically significant factors that influence the perception of charcoal consumption are the same as in the previous model: Living in the urban section of the district (*urban*), the quantity of feed consumed by chickens (*feed_consumed*), and elevation at which the coop is built (*elevation*). However, the partial proportional odds model revealed further where the greatest effects were. Thus, for *urban*, farmers who live in the rural section of the district were more likely to perceive that they were using higher quantities of charcoal than their peers who live in rural sections in general, but the greatest effect was to move farmers away from the lowest value of perception. Likewise, the overall effect of the quantity of feed consumed by chicken (*feed_consumed*) was that farmers are more likely to perceive that they are using more quantities of charcoal. However, the greatest effect of *feed_consumed* was to move farmers from the middle values of perception. Lastly, farmers who live in higher altitudes were more likely to feel that they are using more charcoal in general, but the greatest effect of elevation was to push farmers away from the lowest category of perception.

Factors influencing the perception of water consumption

Proportional Odds Model (POM) results of the perception of water consumption (Table 1-7 in appendix) indicate that only the food insecurity index (*FIES)* was found significant. This suggests that farmers who are more food insecure than their peers are more likely to feel that they are using more quantity of water than what they used before the project started.

As was the case for the perception of charcoal, mathematically, the intercept 1|2 corresponds to logit[$P(Y \leq 1)$], which can be interpreted as the log of odds of perceiving that one is using ‘Much less water’ versus perceiving that one is using ‘Less water’. Likewise, the intercept 2|3 corresponds to logit[$P(Y \leq 2)$]. It can be interpreted as the log of odds of perceiving that one is using ‘Less water’ versus perceiving that one is using ‘The same amount’ and so on.

Partial Proportional Odds Model (PPOM)

Since effects on the variable (*FIES*) were allowed to vary in the partial proportional odds model, they will be interpreted a little differently. As was the case in the proportional odds model, results from the partial proportional odds model (Table 1-2) indicate that farmers who are food insecure were more likely to perceive that they were using higher quantities of charcoal than their peers who were relatively less food insecure. However, the partial proportional odds model further revealed that the greatest effect was to move farmers away from the highest value of perception.

Table 1-1: Results of Partial Proportional Odds Model for Perception of Charcoal Consumption from Farmers (n=323) in Musanze district, 2019

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept):1	-17.660	10.127	-1.744	0.081
(Intercept):2	-11.066	2.915	-3.796	0.000
(Intercept):3	-11.560	2.734	-4.228	0.000
(Intercept):4	-4.978	3.683	-1.352	0.177
age	-0.005	0.012	-0.401	0.688
gender	0.273	0.245	1.116	0.264
urban:1	4.152	1.884	2.204	0.028**
urban:2	2.373	0.600	3.954	0.000***
urban:3	2.473	0.564	4.384	0.000***
urban:4	0.962	0.744	1.293	0.196
ubudehe	-0.229	0.191	-1.203	0.229
FIES	0.024	0.051	0.476	0.634
education	0.015	0.077	0.193	0.847
feed_consumed:1	0.004	0.004	1.142	0.254
feed_consumed:2	0.005	0.001	4.124	0.000***
feed_consumed:3	0.004	0.001	4.411	0.000***
feed_consumed:4	0.002	0.001	1.616	0.106
elevation:1	0.009	0.004	2.026	0.043
elevation:2	0.005	0.001	4.016	0.000***
elevation:3	0.005	0.001	4.400	0.000***
elevation:4	0.001	0.001	0.620	0.535

*Dependent variable: Perception of charcoal consumption; Number of observations: 323; **Significant at p< .05; ***Significant at p < .001.*

Table 1-2: Results of Partial Proportional Odds Model for Perception of Water Consumption from Farmers (n=323) in Musanze district, 2019

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept):1	5.927	2.818	2.103	0.035
(Intercept):2	4.197	2.538	1.654	0.098
(Intercept):3	4.197	2.538	1.654	0.098
(Intercept):4	-1.366	2.487	-0.549	0.583
age	0.007	0.013	0.562	0.574
gender	0.250	0.255	0.979	0.327
urban	-0.329	0.502	-0.655	0.512
ubudehe	-0.009	0.200	-0.045	0.964
FIES:1	0.041	0.402	0.103	0.918
FIES:2	0.220	0.221	0.996	0.319
FIES:3	-0.217	0.130	-1.673	0.094
FIES:4	0.335	0.057	5.845	0.000***
education	-0.008	0.079	-0.104	0.917
feed_consumed	0.000	0.001	-0.550	0.582
elevation	0.000	0.001	-0.140	0.889

*Dependent variable: Perception of water consumption; Number of observations: 323; **Significant at p< .05; ***Significant at p < .001.*

Discussion

As results revealed, *urban*, *feed_consumed*, and *elevation* variables were associated with the perception of charcoal consumption. Results from the analysis (Table 1-6 and Table 1-1) showed that farmers who live in the urban section of the district are more likely to feel that their consumption of charcoal has increased since the project started. As the majority of farmers who live in the urban section of the district normally use less charcoal than those living in rural sections, it may not be a big surprise for those living in the urban area to feel that their consumption has increased. In contrast, farmers who live in rural sections of the district are used to using charcoal in their everyday life and they may not feel that their use has changed. This finding is supported by findings from other studies that found the farmers' location to be an important factor in their perceptions of natural resources (Moges & Taye, 2017).

Regarding *feed_consumed*, results reveal that farmers whose chickens consume more quantity of feed tend to perceive that they use higher quantities of charcoal than before the project started. Since charcoal is used for heating in the brooding activity, it is possible that chickens that consume more feed require more heating as they need the energy to convert the feed into meat. Literature suggests that temperature is an important factor in broiler feed conversion (Aviagen, 2011).

Lastly, farmers who live in higher altitudes are more likely to perceive that they are using larger quantities of charcoal than before the project started. This perception may arise from a higher demand for more charcoal to keep the chickens warm in lower temperatures, which are typical of higher altitudes. Therefore, farmers may feel that they are using higher quantities of charcoal.

According to the results of the perception of water consumption (Table 1-7 and Table 1-2), the food insecurity index (*FIES)* was the only variable that was found significant. This suggests that farmers who are more food insecure than their peers are more likely to feel that they are using more quantity of water than what they used before the project started. Since farmers who are food insecure may not have easy access to water resources, it may be easy for them to feel the burden to use water resources to tend to chickens. As a result, they may feel that they are using more water resources than they used to use before the project started. The link between food insecurity and perception of natural resources among farmers was also found by (Ntuli et al., 2019)

Although both water and charcoal are natural resources, they were not found to be associated with the same factors. *Age, gender, education,* and *ubudehe* were not found to have any significant relationship with either the perception of water consumption or the perception of charcoal consumption.

Conclusions

Since this study investigated perceptions of natural resource consumption, it is worth acknowledging that these are perceptions of resource consumption, not exact measures of resource consumption. Therefore, overestimation or underestimation of natural resource consumption can occur. Examples of overestimation and underestimation of water consumption (Attari, 2014; Fan et al., 2014) or energy consumption (Attari et al., 2010) exist. Consequently, although results indicated that the consumption of natural resources has increased, the conclusion on whether actual consumption has increased will require further investigation. Future studies can further assess whether the actual consumption of natural resources has changed and the factors that influence that change.

Nonetheless, although perceptions of natural resource consumption from respondents may differ from the actual natural resource use, they are still important because they can inform better management of resources (Fernández-Llamazares et al., 2016). Furthermore, although the majority of farmers feel that their consumption of resources has increased since the project started, it is crucial to note that there might be many factors that may have contributed to the increased consumption of resources; some may be related to the project while others may not be related to the project.

As research suggests, people who accurately understand their resource consumption patterns may be more likely to conserve them since they are aware of how much they are consuming (Fan et al., 2014). To encourage behavior change towards sustainable consumption of natural resources, we need to start by assessing people's perceptions of their consumption of natural resources.

This study recommends that the management of natural resources be integrated into the design of food security projects such as the TI project. Furthermore, food security programs can benefit from tracking farmers' actual consumption of natural resources. This could allow more accurate measures of how much farmers consume, thus increasing the likelihood to conserve natural resources.

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Appendix

Table 1-3: Brant test

Test for	X2	df	probability
Omnibus	39.31	24	0.03**
age	2.73	3	0.44
gender	2.02	3	0.57
urban	4.51	3	0.21
ubudehe	5.85	3	0.12
FIES	19.16	3	0.00***
education	3.36	3	0.34
feed_consumed	4.73	3	0.19
elevation	3.72	3	0.29

*Brant test: Perception of charcoal consumption; Number of observations: 323; **Significant at p< .05; ***Significant at p < .001.*

Table 1-4: Summary of results on farmers' perception of natural resource consumption in Musanze district

	Responses	Meaning		Frequency	%
Perceptions of water consumption	1	Much less water		1	0.31
	2	Less water		3	0.93
	3	Same amount		9	2.79
	4	More water		206	63.78
	5	Much more water		104	32.20
			Total	***323***	***100.00***
Perceptions of charcoal consumption	1	Much less charcoal		6	1.86
	2	Less charcoal		54	16.72
	3	Same amount		14	4.33
	4	More charcoal		212	65.63
	5	Much more charcoal		37	11.46
			Total	***323***	***100.00***

Table 1-5: Summary of descriptive statistics by sector

Variable	Response	Meaning	Gataraga	Kinigi	Muhoza
Mean values for continuous variables and (Standard deviation)					
Age		Mean age (years)	41.25 (10)	38.51 (10)	40.95 (12)
Feed consumed		Mean quantity of feed consumed by chickens per cycle (kgs/cycle)	652.21 (158)	509.93 (130)	588.37 (154)
Elevation		Mean elevation at which the coop is located (m)	2152.40 (112)	2440.93 (17)	1825.61 (44)
Count of categorical variables					
Education	1	None	0	3	1
	2	Some primary	41	25	9
	3	Completed primary (1-6)	40	22	19
	4	Vocational school	0	1	0
	5	Some secondary	36	28	25
	6	Completed secondary (7-12)	23	6	28
	7	Some university	1	0	3
	8	Completed university	4	1	7
	9	Graduate school	0	0	0
Gender	0	Male	87	42	32
	1	Female	58	44	60
Ubudehe	1	1 = lowest income, 4 = highest income	17	6	6
	2		68	31	53
	3		60	49	32
	4		0	0	0
FIES (Food insecurity index)	0	0 = food secure, 6 = food insecure	57	40	27
	1		14	4	4
	2		14	10	2
	3		13	6	7
	4		10	7	21
	5		15	4	16
	6		22	15	15

Number of observations: 323

Table 1-6: Results from the proportional odds model for the perception of charcoal consumption

	Value	Std. Error	t value	p-value
age	-0.00597	0.011507	-0.51902	0.604
gender	0.268637	0.243764	1.10204	0.270
urban	2.108462	0.306663	6.875506	0.000***
ubudehe	-0.22403	0.186912	-1.19859	0.231
FIES	0.023348	0.050215	0.464971	0.642
education	0.011791	0.076024	0.155091	0.877
feed_consumed	0.003628	0.000701	5.174671	0.000***
elevation	0.00364	0.000332	10.97536	0.000***
1|2	5.765135	0.046543	123.8678	0.000
2|3	8.384792	0.376832	22.25077	0.000
3|4	8.680189	0.380791	22.79513	0.000
4|5	12.2641	0.448451	27.34771	0.000

*Dependent variable: Perception of charcoal consumption; Number of observations: 323; **Significant at p< .05; ***Significant at p < .001.*

Table 1-7: Results from Proportional Odds Model for the perception of water consumption

	Value	Std. Error	t value	p value
age	0.006934	0.012291	0.564185	0.573
gender	0.239364	0.243963	0.98115	0.327
urban	-0.32759	0.27977	-1.17091	0.242
ubudehe	-0.02505	0.201882	-0.12409	0.901
FIES	0.266318	0.05435	4.900095	0.000***
education	-0.00741	0.076372	-0.09696	0.923
feed_consumed	-0.00044	0.000754	-0.58189	0.561
elevation	-0.00013	0.000362	-0.35637	0.722
1|2	-5.62378	0.05337	-105.373	0.000
2|3	-4.22859	0.203619	-20.7671	0.000
3|4	-3.03083	0.353134	-8.58267	0.000
4|5	1.10616	0.436373	2.534895	0.011

*Dependent variable: Perception of water consumption; Number of observations: 323; **Significant at p< .05; ***Significant at p < .001.*

CHAPTER II
INVESTIGATING ENVIRONMENTAL BEHAVIORS – A CASE STUDY OF FARMERS IN RWANDA

Abstract

One of the challenges facing humanity is how to increase global food production while protecting the environment. Meeting this challenge requires a better understanding of farmers' behaviors, especially those affecting the environment. While most theories attempt to explain environmental behaviors separately, an integrated framework can provide a better understanding. However, very few studies have integrated the various theories to improve our understanding of environmental behaviors among farmers. This study employed theories of behavior to examine the influence of attitudes, subjective norms, perceived behavior control, and other factors on farmers' behavioral intent to engage in environmental behaviors. In particular, the study focused on three environmental behaviors: rainwater harvesting, the use of organic fertilizer, and the use of alternative sources of energy for domestic cooking. To conduct the study, a survey was conducted from a randomly selected sample of 604 farmers from 7 sectors of the district of Musanze in northern Rwanda. A Structural Equation Model (SEM) approach was used to analyze data. Results revealed that farmers' decision to engage in environmental behaviors depends on their attitudes, social norms, perceived behavior control, and other background factors. As results showed, however, the influence of factors and the direction of the influence can vary depending on the behavior considered. Overall, the results provided useful insights into understanding farmers' decision-making towards nature and the environment and, as a result, provided policy options on adopting more environmentally-friendly behaviors among farmers.

Keywords: Environmental behaviors; Rainwater harvesting; Organic fertilizer; Alternative sources of energy; Structural Equation Model; Rwanda

Introduction

Background of the study

The demand for food continues to grow globally. The rising food demand is primarily a result of the growing population and the soaring demand for animal-sourced foods (Alexandratos & Bruinsma, 2012; World Resources Institute, 2018). To meet the challenge of feeding everyone, FAO (2009) estimates that food production will have to increase by 70% by 2050. Increased production, however, is likely to place further pressure on natural resources (Alexandratos & Bruinsma, 2012) and can lead to environmental degradation (Donohoe, 2003). Evidence suggests that agricultural activities lead to adverse effects on air quality and climate (Aneja et al., 2009); water quality and soils (Bruland et al., 2003); biodiversity (Medan et al. 2011); ground-water (Hamilton & Helsel, 1995). The challenge, then, is not simply to feed the world but to do it while preserving the environment. Reconciling food production systems with natural resources offers an opportunity to address the challenge. One possible approach to attain this reconciliation consists of applying sustainable agriculture practices (Robertson & Swinton, 2005). These practices include practices such as crop rotation, soil management, nutrient management, and integrated pest management (Horrigan et al., 2002).

Meeting the challenge of sustainably feeding the world will also depend on our choices and behaviors. The state of the environment or natural resources can be determined by our food choices and behaviors. To illustrate this, Leach et al. (2012) observed that choices such as food consumption have a considerable impact on the amount of nitrogen that ends up in the environment. By eliminating certain behaviors, as McLaughlin and Kinzelbach (2008) argue, the global society could balance food production and protection of the environment; these behaviors may include: maintaining our high demand for high-calorie animal-based diets; degrading our soils; releasing nutrients and pesticides into nature; high volumes of food waste and loss; practicing unsustainable and unsafe irrigation. However, some practices are not easy to eliminate. For example, it is unlikely that people will be willing to give up meat consumption despite the benefit of that behavior on natural resources (Odegard & van der Voet, 2014). The complex relationship between behaviors, food consumption, and natural resources highlights the importance of a better understanding of environmental behaviors in the context of agricultural production and food consumption. Consequently, the dual goal of food security and natural resources integrity demands behavioral insights.

Traditionally, interventions that involved behavioral insights were applied to consumers and the public in general. These behaviors may involve the choice of the food you eat or the choice of how much energy to consume per day (Thaler & Sunstein, 2008). However, interventions that are informed by consumers' behaviors do not necessarily reflect the reality of farmers' behaviors in agricultural systems. As Dessart et al. (2019) argue, farmers' decisions to adopt sustainable practices, for example, may require long-term thinking or commitment, thus farmers' behaviors should be treated differently. Current literature shows that determinants of farmers' environmental behaviors fall under three categories: psychological determinants (Bijani et al., 2017; Quinn & Burbach, 2017), socioeconomic determinants (Blankenberg & Alhusen, 2018; Janmaimool & Denpaiboon, 2016), and physical determinants (Garekae et al., 2016). Studies on every category have been conducted in different parts of the world (e.gs., Fang et al., 2018; Gadenne et al., 2011; Gilg & Barr, 2006; Napier & Brown, 1993).

Rwanda and the use of fertilizer, energy use for domestic cooking, and rainwater harvesting

The present study investigates farmers' environmental behaviors in Rwanda. In particular, the study investigates the determinants of three specific behaviors: rainwater harvesting, fertilizer use, and the use of energy sources for domestic cooking.

Fertilizer use: The agriculture sector in Rwanda is dominated by smallholder farmers, but their productivity remains low. Agricultural intensification offers an opportunity to improve productivity in a country like Rwanda where arable land is limited, thus addressing poverty, food insecurity, and malnutrition (IFDC, 2014). The Government of Rwanda (GoR) has developed the Strategic Plan for Agriculture Transformation (SPAT) to raise annual agricultural growth to 6 percent or more and allocate at least 10 percent of the national budget to agriculture. Part of the SPAT is to increase fertilizer use, and the GoR has developed the fertilizer market and supports fertilizer utilization. This has resulted in a significant increase in nationwide fertilizer use, from 6,000 metric tons in 2006 to 34,000 metric tons in 2012. During these 6 years, the penetration rate (the number of farmers using fertilizers) has increased from 14 to 29% (MINAGRI, 2012). Recent data show that around 68% of farmers applied inorganic fertilizers during one of the agriculatural seasons (NISR, 2021). However, the returns of increased use of fertilizer and its agricultural productivity do not reflect environmental consequences (Uri, 1997). The adverse effects of fertilizers on the environment include algae blooms (which deplete oxygen in surface waters), pathogens and nitrates in drinking water, and the emission of odors and gases into the air (Berg et al., 2017). Other adverse effects include greenhouse gas emissions (methane and nitrous oxide), groundwater pollution with nitrates, and heavy-metal buildup in the soil (Lenka et al., 2016).

Energy use for domestic cooking: Rural households in Rwanda still rely on biomass consumption due to the scarcity of energy source options. Slander and Hendriksen (2012) reported that as of 2011, approximately 86% of primary energy in Rwanda came from biomass, mainly in the form of wood; wood is either used directly as fuel (57%) or converted into charcoal (23%) together with smaller amounts of crop residues and peat (6%). Although the dependence on biomass has improved over the past two decades (from 95% to 86%), the ratio is still high (Bimenyimana et al., 2018). The use of charcoal in rural areas of Rwanda is guaranteed to increase as these regions urbanize, and household incomes increase (Marge, 2009). In particular, one of the challenges facing Rwanda's energy sector is to produce and consume biomass-based energy without harming the environment (Munyaneza et al., 2016).

Unfortunately, the heavy dependence on biomass is intrinsically damaging to the environment in general, and forests in particular (Bimenyimana et al., 2018; Mazimpaka, 2014). As charcoal relies heavily on forest resources more than fuelwood, dependence on biomass is more concerning in the case of charcoal (Girard, 2002). The use of charcoal and other biomass fuels can be detrimental to health as well. Inefficient cooking practices that rely on solid biomass, including charcoal, can lead to household air pollution (HAP), which is the largest global environmental risk factor for disease burden (Forouzanfar et al., 2015). The inefficient use of solid fuels for cooking contributes to 3.8 million premature deaths every year. Exposure to HAP is known to be higher for women and children than men and more prevalent in low- and middle-income countries (WHO, 2018). The high prevalence among women is explained by the fact that women do most cooking and are taking care of the kids at the same time. The adverse effects of biomass use on human health and the environment necessitate a reduction in biomass consumption as a fuel.

Increased use of biomass such as charcoal can be reduced by transitioning to more efficient alternative technologies. In Rwanda, for example, technologies that have the potential to reduce the consumption of charcoal include improved cookstoves, efficient charcoal production, efficient energy alternatives like biomass pellets, liquefied petroleum gas (LPG), and biogas. These technologies can be coupled with better forestry management and more incentives for small producers of charcoal (MININFRA, 2016). Proposing alternative solutions to charcoal reduction is not enough; people need to adopt them. As is often the case, however, these technologies are often met with low adoption rates. When Jagger and Das (2018) reviewed an experience of a for-profit firm in Rwanda, they found that only 38% of households marketed to as part of an impact evaluation study adopted the pellet and the improved cooking stove system. Furthermore, approximately 45% of those who adopted terminated their contracts after signing up.

Water use: One of the challenges facing Rwanda is water scarcity. The daily per capita consumption of water was around 13 liters per day in 2010 in Rwanda, a quantity that fell below the envisaged standard consumption of 20 liters (MININFRA, 2013). In the northern part of Rwanda, the average water consumption per capita was reported to be between 4.7 and 12.3 liters per day, and some residents collected water from more than 1,000 meters from their households or spent more than 30 minutes to collect water (Nkurunziza, 2016). While Rwanda has made progress in improving water supply, projections continue to show a further increase in water demand (MININFRA, 2013; UNEP, 2010). The projected increase in water demand is based on factors such as population growth, urbanization, rapid economic development, and decreasing mortality rate (MINIRENA, 2012). Moreover, agriculture continues to place further demands on water resources, particularly, intensification and industrialization (NISR, 2019). Agriculture consumes more water than any other sector in Rwanda (over 65%) (Bizuhoraho et al., 2018). Although much of water consumption in agriculture comes from irrigation activities, data suggest that livestock development, especially cattle, consumes water resources to an appreciable degree (MINIRENA, 2012).

As water use increases, especially in agriculture, environmentally friendly behaviors such as water conservation can be an important solution to water scarcity (Rockström et al., 2009). Additionally, agricultural water management in agriculture can improve agricultural productivity, which can lead to a reduction in poverty and an end to hunger in developing countries like Rwanda (FAO, 2017). In studying the effects of water conservation measures on maize yield in Rwanda, Uwizeyimana et al. (2018) found a strong correlation between water conservation methods and maize yield in drought-prone agricultural zones. Additionally, the study revealed that irrigation through rainwater harvesting was a more promising measure for maize growers to stabilize agricultural production as well as mitigate the dry spells.

However, the main hurdle to the implementation of water conservation practices is that it often depends on public willingness to adopt these behaviors (Hurlimann et al., 2009). In the case of farmers, for example, it is important to understand whether they are willing to conserve water resources. This is often achieved by understanding farmers' intention to conserve water as environmentally-oriented intention can often predict environmental action (Corbett, 2002; Yazdanpanah et al., 2014). Generally, pro-environmental people tend to see the need for water conservation, thus considering it an important aspect of environmental protection and stewardship. This stems from a significant relationship that exists between pro-environmental behavior and water conservation behavior (Adams, 2014).

Objectives, justification, and scope of the study

The primary goal of this research is to investigate the determinants of environmental behaviors among farmers in Rwanda. Specifically, the study seeks to (1) assess the role of psychological factors (attitude, subjective norms, and perceived behavioral control) in determining behavioral intent and (2) examine the relationship between behavioral intention and socio-economic factors as background factors.

The results of this research will contribute to the current literature by employing an integrated framework for modeling farmers' environmental behaviors based on two existing theories: The Theory of Planned Behavior and the Reasoned Action Approach. More specifically, the results from the study will provide a better understanding of how psychological and socio-economic factors (as background factors) play an important role in shaping farmers' behavioral intent to engage in environmental behaviors. Lastly, the results of the study will provide policy options for adopting more environmentally friendly behaviors among farmers.

This study will investigate environmental behaviors in the context of the Theory of Planned Behavior and the Reasoned Action Approach. The present study does not attempt to apply other behavior theories. Furthermore, the study does not intend to cover all environmental behaviors among farmers in Rwanda. Instead, this study focused on the following environmental behaviors: rainwater harvesting, fertilizer use, and the use of alternative sources of energy for domestic cooking.

Theoretical Framework

For years, the Theory of Planned Behavior (TPB) has been used to predict and explain behaviors. The TPB started as the Theory of Reasoned Action (TRA), which attempted to predict people's intention to engage in behavior by explaining the link between attitudes, norms, and behaviors within human action (Ajzen & Fishbein, 1977). The assumption was that people behave according to their attitudes, norms, and behavioral intentions. Moreover, the authors argued that people's decisions to engage in a given behavior depend on the expected outcome of their actions. However, TRA did not include some factors that authors came to believe were important in explaining behaviors. For example, TRA did not include the notion of perceived control – it only focused on attitudes and norms. Consequently, the authors revised TRA and expanded it to address those limitations. The first iteration to improve the TRA became to develop the TPB, which included the notion of perceived control (Madden, Ellen, & Azjen, 1992). As such, TPB became an improved theory developed to explain behaviors through the intention to engage in a given behavior (Azjen, 1991).

As the key factor in TPB, behavioral intent is the basis for an individual's motivation to perform a given action. Thus, the stronger the intention to engage in a given behavior, the more likely to engage in that behavior. Furthermore, the theory suggests that three predictors determine intention: attitudes, subjective norms, and perceived behavioral control. Attitudes in this context mean the evaluation (favorable or unfavorable) that individuals make towards the behavior to be performed. Subjective norms refer to perceived social pressure to engage in a given behavior. Perceived behavior control refers to people's perceptions of their ability to perform a given behavior (Azjen, 1991; Madden et al., 1992). According to the TPB, engaging in the behavior is done mainly through intentions. Intentions, in turn, are determined by attitudes, subjective norms, and perceived behavioral control (Azjen, 1991; Madden et al., 1992).

Despite its extensive use in behavior studies, TPB has limitations. Although it thoroughly explains the internal factors that shape behaviors through intention and perceived behavioral control, it does not explicitly include certain factors that may affect behaviors (Si et al., 2019). The lack of some external factors in TPB has been recognized in some environmental behavior studies. For example, when studying the intentions of rural landowners to engage in riparian improvement programs, Corbett (2002) recognized that external and social constraints such as financial constraints were not included in the TPB despite their importance in explaining behaviors. The study suggests the use of improved models that include external factors in TPB.

To address the lack of external factors in TPB, a new approach was suggested: Reasoned Action Approach (RAA). This approach focuses on the origin of behavioral, normative, and control beliefs. Behavioral beliefs refer to the link or association that individuals establish between given behaviors and the outcomes or attributes of these behaviors. Normative beliefs refer to the likelihood that other individuals or groups will approve or disapprove of one individual's behavior. Control beliefs refer to the presence or absence of requisite resources and opportunities (Azjen, 1991). As is the case in TPB, it is these beliefs that determine attitudes, subjective norms, and perceived behavioral control, which in turn determine the intention and ultimately behavior (Ajzen, 2012). According to RAA, these beliefs stem from several background factors, which may include demographics, socioeconomic status, age, group membership, past experiences, and others (Fishbein & Ajzen, 2010). Although Fishbein and Ajzen (2010) suggested potential background factors that may influence behaviors through beliefs, the choice of factors may be informed by specific knowledge of the area of research as these may change from one specific case to another.

Including background factors in the TPB, via RAA, was an advancement in further explaining human behavior. However, TPB still needs to clearly show how factors such as the physical environment can explain human behavior, together with other background factors such as personal and socio-economic factors. For example, there exists no published documentation of geographical or environmental factors as part of the background factors in RAA. A review of the application of TPB in environmental science suggested that future research needs to use theories that include external factors to improve both prediction and implications of environmental behaviors (Si et al., 2019). One theory poised to address the lack of physical environment as an external factor in explaining environmental behavior is known as the Social Cognitive Theory (SCT).

The SCT explains behaviors by emphasizing how behaviors, personal factors, and environmental factors influence each other (Bandura, 1989). The central argument of the SCT is the idea of personal agency, which is the ability of individuals to intentionally choose, execute, and manage their actions to attain expected outcomes. Personal agency can be exercised through a mechanism known as self-efficacy, which is the belief in the ability to attain expected outcomes. The idea of self-efficacy is likened to the idea of perceived behavioral control of the TPB (Fishbein & Ajzen, 2010). According to the SCT model, the behavior is shaped through the interaction of individuals' personal factors and environmental factors in what was called a triadic causal model (Bandura, 1999).

Several studies have applied the SCT to explain environmental behaviors. For example, Sawitri et al. (2015) applied the model to study pro-environmental behavior. The results of the study revealed that people with high environmental self-efficacy engaged in pro-environmental behavior more than those with a lower perception of self-efficacy. Similarly, Preko (2017) used the theory to study green consumer behavior in Ghana. Particularly, the study tested the triadic interactions of consumer behavior, personal factors, and environmental factors. The results of the study indicated that personal factors had a positive relationship with green consumption behavior that also influences environmental degradation, thus conforming to the model. However, like TPB, SCT cannot explain environmental behaviors fully on its own. As Akintunde (2017) argued, integrated frameworks of behavioral theories can be invaluable in addressing environmental challenges.

An integrated model of environmental behavior can address the difficulty that results from relying on one single model of environmental behavior (Akintunde, 2017; Si et al., 2019). Environmental behaviors, for example, cannot be easily explained by one single behavior theory; instead, integrated frameworks should be used to explore different factors that determine environmental behaviors (Blankenberg & Alhusen, 2018). These frameworks can integrate cognitive, socio-economic, and other factors such as physical or environmental factors.

So far, very few studies have attempted to use the TPB-SCT integrated framework to explain behaviors. However, none of these studies are in environmental science research. For example, Poobalan et al., (2012) used the integrated approach to investigate physical activity attitudes, intentions, and behavior among 18–25-year-olds. In addition to this study, Poobalan et al. (2014) integrated both TPB and SCT to study diet behavior among young people in transition to adulthood. Similarly, Sousa-Ribeiro et al., (2018), used the integrated framework to investigate the intentions of older unemployed people in training programs.

However, to date, no published study has integrated TPB and SCT to explain environmental behaviors, especially in the context of farmers' behaviors. This study seeks to integrate TPB and SCT to explain environmental behaviors among farmers in northern Rwanda.

Environmental behaviors

Environmental behaviors, also known as pro-environmental behaviors, are individual behaviors that contribute to the sustainability of the environment and natural resources. These behaviors include engaging in activities such as limiting energy consumption, reducing waste or recycling (Mesmer-Magnus et al., 2013), engaging in waste management (Janmaimool & Denpaiboon, 2016), purchasing organic food (Voon et al., 2011), water conservation (Trumbo & Keefe, 2011), engaging in forest conservation efforts (Garekae et al., 2016) and others. Individual environmental behaviors may be public or private. Public environmental behaviors may include choosing public transportation instead of using your car or taking part in a communal activity such as an environmental rally. Private environmental behaviors may include activities like composting or choosing not to use air conditioning whenever possible (Ones et al., 2015).

The distinctive aspect of individual environmental behaviors is that they are intentional and voluntary. However, it is important to acknowledge that in some instances people may be prompted to engage in environmental behavior such as recycling because they can get in trouble if they do not comply with certain regulations. Nonetheless, it is worth positing that even in the presence of social or governmental structures that may facilitate or hamper environmental behaviors, ultimately the decision to engage in a given environmental behavior can be a personal choice (Mesmer-Magnus et al., 2013; Ones et al., 2015).

Determinants of environmental behaviors

Psychological and cognitive determinants

TPB has been applied to investigate environmental behaviors. For example, Wang et al., (2019) found that intention was the most critical factor in explaining farmers' behaviors in controlling non-point source pollution in water source protection areas in China. In addition to water resources, TPB has also been used in other environmental areas such as recycling (Cheung et al., 1999), water conservation (Trumbo & Keefe, 2011), and green consumerism (Sparks & Shepherd, 1992). Intention to behave in a given way is determined by attitudes, subjective norms, and perceived behavioral control (Azjen, 1991; Martin Fishbein & Ajzen, 2010; Madden et al., 1992). As such, it is important to explore what influences intention (see Figure 2-1).

Attitude: Attitude refers to the evaluation (favorable or unfavorable) that individuals make towards the behavior to be performed (Azjen, 1991). Attitude can be shown to correlate with environmental behaviors. Quinn and Burbach, (2017) showed a strong relationship that exists between farmers' conservation practices that affect surface water quality and personality characteristics, including environmental attitude. Likewise, the attitude variable was found to be the most important predictor of soil conservation behavior in a study done by Bijani et al. (2017) in Iran.

Subjective norms: subjective norms describe the perceived influences or pressures from other people to engage in a given behavior (Azjen, 1991). For instance, concerning environmental behaviors, the likelihood of adopting an environmentally responsible behavior can be higher if people who are close to you (such as parents, friends, or siblings) expect you to behave that way (Yoon et al., 2010). Cialdini et al. (1990) distinguished between the injunctive norm, which is the perception of what others think should be done, and descriptive norm, which is the perception of what most people do. Farrow et al. (2017) further group descriptive and injunctive norms into social norms or simply norms.

Perceived behavior control: Perceived behavioral control is the ability to decide at will whether to engage in a given behavior or not (Azjen, 1991; Madden et al., 1992). Literature shows the relationship between perceived behavior control and environmental behavior. For example, de Leeuw (2015) applied the TPB to identify key determinants underlying pro-environmental behavior in high-school students. The results demonstrated that the role of perceived behavioral control in explaining students' eco-friendly behaviors was noteworthy. Additionally, while exploring the relationship between Australians' perceptions of climate change, its impact on the Great Barrier Reef, and predictors of environmentally responsible behavior, Yoon et al. (2010) found that perceived behavior control was the strongest predictor of environmental behavior.

Socio-economic factors

Socio-economic factors in this study will be discussed in the context of the new model of the TPB as developed by Fishbein & Ajzen (2010). Thus, socioeconomic factors will be understood to be background factors to determinants of behaviors: attitudes, subjective norms, and perceived behavior control. These background factors are indirectly linked to behaviors through beliefs (behavioral, normative, and control). In this sense, these factors should be understood as indirect factors to behaviors. The following are some of the factors in the literature.

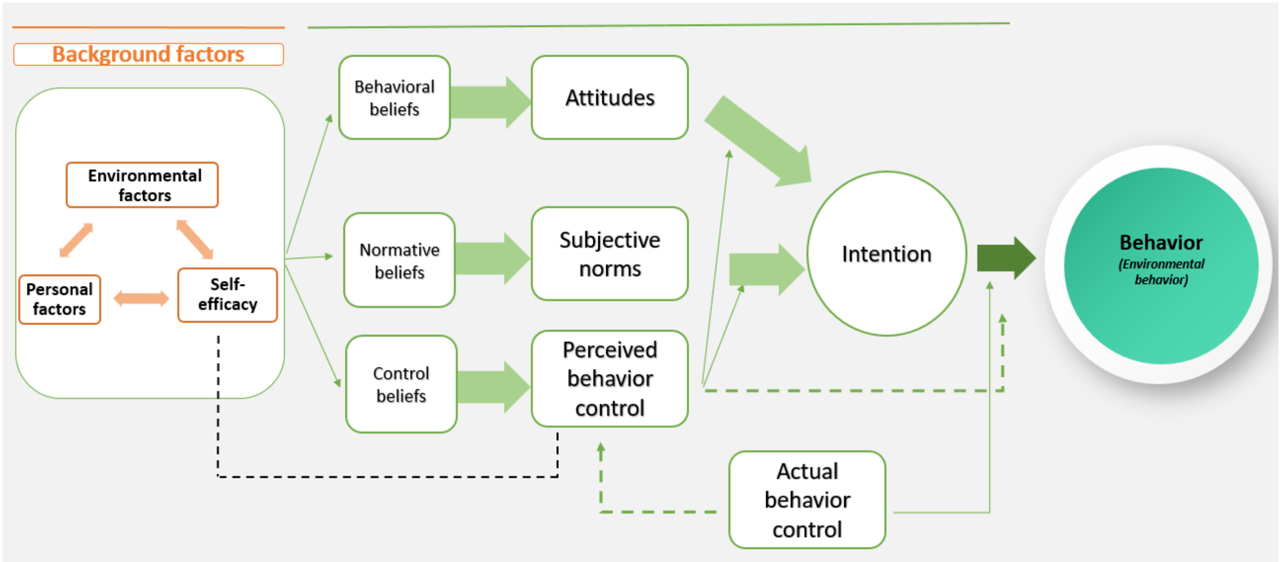

Figure 2-1: Proposed Theoretical Framework

Age can influence farmers' behaviors towards natural resources and the environment (Raudsepp, 2001). For instance, a positive relationship would suggest that the older people get, the more likely they are to act in favor of the environment. This may result from the tendency for older generations to be more concerned about the environment than the younger generation (Shen & Saijo, 2008). In contrast, age can have a negative relationship with environmental behavior (Bronfman et al., 2015), thus indicating that younger populations tend to have environmentally responsible behaviors (Jones & Dunlap, 1992). Furthermore, the relationship between age and environmental behavior may change based on the type of behavior. For instance, Diekmann and Preisendorfer (1999) explored four different categories of environmental behaviors: recycling, shopping, energy, and transport. The study found a negative relationship between age and recycling, shopping, and energy but a positive relationship with transport.

Education can also be an important factor in predicting environmental behavior. The more educated a person is the more likely they are concerned about the environment (Raudsepp, 2001; Shen & Saijo, 2008). For example, Traore et al. (1998) reported that farmers who had higher educational attainment were more likely to engage in conservation practice. In some instances, education can be found to exert more influence on environmental behavior than other factors (Longhi, 2013) because education can increases knowledge about environmental issues (Franzen and Meyer, 2010).

Gender was also shown to play an important role in determining environmental behavior (Blankenberg & Alhusen, 2018; Vicente-Molina, Fernández-Sainz, & Izagirre-Olaizola, 2018). Women are known to have a higher likelihood to behave in favor of the environment (Lynn and Longhi, 2011). For example, Janmaimool and Denpaiboon (2016) studied the determinants of villagers' engagement in pro-environmental behavior in Thailand and found that women were more likely to engage in waste management behavior than men. Furthermore, differences in environmental behaviors among gender can also depend upon the type of behavior. For instance, women tend to be more environmentally responsible for home-based behaviors such as recycling, while men exhibit environmental behaviors towards external activities such as joining a group (Johnson et al., 2004).

Income – similar to age, education, and gender – can be a predictor of environmental behavior (Blankenberg and Alhusen, 2018). Shen and Saijo (2008) found a positive relationship between income and environmental concerns. This may lead to people with higher income engaging more in environmental behavior than their peers. For instance, Poortinga et al. (2004) found a positive relationship between income and energy use. Similarly, Gadenne et al. (2011) found that people with low income are less likely to engage in environmental behaviors than their peers. By contrast, income may be negatively related to environmental concerns (Cottrell, 2003). Consequently, people with higher incomes may not be willing to engage in environmental behaviors.

Land ownership can also be shown to influence farmers' environmental behaviors. For instance, Lawin and Tamini (2019) demonstrated that land ownership increased environmental practices among farmers in Benin. Moreover, Mao et al. (2021) revealed that cotton farmers in China were more likely to use green production practices such as the use of fertilizer when they had stable ownership of the land. This may suggest that farmers might be interested in using environmental practices on lands they know they own or hold for some time as opposed to lands they know will be transferred to someone else soon.

Materials and Methods

Study area

This study was conducted in one of the five districts – and the capital – of the northern province of Rwanda: Musanze district. On a surface area of 530 km^2 (200 sq mi), the Musanze district is home to 368,000 people, with a population density of 694/km^2 (1,900/sq mi). Musanze population represents 3.9% of the total population of Rwanda and 21.3 % of the Northern Province population (MINECOFIN, 2015; NISR, 2013). The district comprises 15 administrative sectors, 68 cells, and 432 villages. Of all the sectors, Muhoza is the most populated sector with 51,878 residents and the least populated sector is Nkotsi with 13,546 inhabitants. Around 266,185 inhabitants of Musanze district (72.3% of the resident population) live in rural areas, making Musanze district predominantly rural. The rest of the population lives in more or less urban sections of the district, with Muhoza being the most urbanized sector of the district (MINECOFIN, 2015). In addition to being rural, the district of Musanze is the most mountainous district in Rwanda with the majority of volcanoes located within the district, specifically, in the Volcanoes National Park. Five out of eight volcanoes in the Virunga chain (Karisimbi, Bisoke, Sabyinyo, Gahinga, and Muhabura) are found in the district, with Karisimbi being the highest point in Rwanda at 4,507m (the sixth tallest peak in Africa). These volcanoes are home to the animal species that make Musanze one of the most visited tourist destinations in Rwanda: mountain gorillas (Rwanda Convention Bureau, 2021; Volcanoes National Park, 2021).

Determining the sample size

Power analysis

Before selecting respondents, the appropriate number of respondents, i.e., the sample, was determined. Among the four major ways to determine or estimate the sample of a study (heuristics, literature review, formulas, and power analysis), power analysis is the more precise in determining an appropriate sample size (Lunenburg & Irby, 2008). Thus, the preferred method to determine the sample for this research was power analysis. Power analysis is conducted to determine the power of a statistical test of a study. Statistical power refers to the probability of rejecting the null hypothesis when it is false – that is, the probability of detecting an effect when it does exist. Statistical power is influenced by three factors: sample size, effect size, and significance criterion. Effect size reflects the strength of a relationship between the independent variable and the dependent variable (Vaske, 2008). It is a quantitative reflection of the magnitude of a given phenomenon (Kelley & Preacher, 2012), which is important when we want to measure not just whether there is a relationship or an effect but also when we want to know how much the effect is. As for the significance criterion, it represents the probability of mistakenly rejecting the null hypothesis, i.e. it represents the risk we are willing to take to make a type I error (Cohen, 1992).

In addition to determining statistical power, one of the most common reasons to conduct power analysis is to determine the sample size required to detect an effect of a given size. When power analysis is done before the study is conducted, it is known as a prospective or *a priori* power analysis (Thomas, 1997). A prospective power analysis can be used to estimate effect size, sample size, significance, or statistical power. However, it is mostly used to estimate the required sample size (Ellis, 2010). Although a prospective power analysis is not the only power analysis that can be used, it is the most common and most recommended as it helps a researcher determine the sample size beforehand and offers unambiguous results (Hoenig & Heisey, 2001;

Levine & Ensom, 2001; Thomas, 1997). As such, this study conducted a prospective power analysis and determined the sample size required to achieve the statistical power.

Power, effect size, and significance criterion for the study

To determine the sample size, it is important to set beforehand the statistical power, the effect size, and the significance criterion (Cohen, 1992). Regarding statistical power, research suggests that it is usually difficult to justify a research study that has a power less than .5 as it is likely to lead to incorrect conclusions – that is, it will likely fail to reject the null hypothesis even when it is false. In contrast, statistical power that is substantially higher than .8, though desirable, is often deemed prohibitively difficult to obtain. Given these two scenarios, most analyses consider a power of .8 to be the desirable level of power (Murphy & Myors, 1998). Thus, this research study set the power at .8.

The next step is to define the effect size. Effect size can be determined in two ways. One way consists of looking at the literature of the current research (where enough studies can be found) and then determining the typical effect size (usually the mean). When this approach cannot be done or is not applicable, the alternative is to follow the conventional definitions of the small, medium, and large effect size and choose one for the current research (Schäfer & Schwarz, 2019). These conventions were proposed by Cohen (1988) and Cohen's d is now a measure of effect size. Cohen's d is the standardized mean difference between two group means. Cohen's d= .2, .5, and .8 denotes a small, medium, and large effect size, respectively. In the case of multiple regression, f2 is used as the effect size index, which is equal to .02 for a small effect, .15 for a medium effect, and .35 for a large effect. When we follow these conventions to determine effect size, it is recommended to base our power analysis on small effect size. This recommendation is based on the fact that a study that has sufficient power to detect small effects will also detect medium and large effects. Conversely, a study that has the power to detect large effects runs the risk of missing small effects. Thus, a study that assumes a small effect size runs little risk of making type I or type II errors (Murphy & Myors, 1998). Accordingly, this research study followed the effect size conventions by Cohen (1988) and chose the small effect size.

Finally, when we have the power and the effect size, the remaining step to determine the sample size is to determine the significance criterion. Often, the decision about the significance criterion is practically limited to the values of .05 versus .01 (Murphy & Myors, 1998). Unless otherwise stated, this value is conventionally set at .05 (Cohen, 1992). Thus, this research set the significance criterion at .05.

Sample size

A statistical power analysis was performed for sample size estimation based on statistical power, significance criterion, and effect size. As determined earlier, the statistical power for this study is .80 while the significance criterion is set at .05). The effect size (ES) in this study is considered to be small using Cohen's (1988) criteria for multiple regression (f2=.02). In addition to these values, the estimation of the sample size for multiple regression depends upon the number of predictors (Faul et al., 2007; Howell, 2010). In the case of this study, the overall number of predictors is 8, with 3 tested predictors of interest – attitude, subjective norms, and perceived behavior control. Using different software packages and resources, we estimated the sample size based on the values above. For example, using the GPower software (version 3.1) by Faul et al. (2009), the estimated sample size needed for this study based on the values above is approximately n = 550. This is close to the value given by the calculation made with the R "pwr" package by Champely (2020): N= 549[3]. The use of the WebPower package (Zhang et al., 2019) in the R software R (R Core Team, 2013) for the sample size estimation resulted in a sample size of n=650[4]. One way to decide could be to use the mean (n=583) but to be safe, the proposed sample size will be the highest of those values as the more data the better power of analysis. Thus, the estimated size of this study was n=650.

Sampling procedures and selection of participants

To select respondents from the study area, this study employed a two-stage cluster sampling, an instance of multi-stage sampling. Usually, multi-stage sampling is used when it is difficult to obtain a sampling frame or when the population is scattered over a wide geographical area (Chauvet, 2015) as was the case for the Musanze district. Another motivation to use cluster sampling was to reduce cost since this technique uses fewer resources unlike other sampling techniques (Legg & Fuller, 2009). The procedure for sampling in this study consisted of three main steps: defining the frame, selecting the clusters from the frame, and finally selecting the respondents from the clusters.

The first step was to define the sampling frame, the purpose of which was to obtain a list of elements of the population (preferably the entire population) that could be sampled. A sampling frame has useful information about the elements of the population, which may include individuals, households, or institutions (Sapsford & Jupp, 2006; Turner, 2008). Between the two most common options for defining a sampling frame, this study chose the area sampling frame. An area frame can be obtained by dividing a geographical area into mutually exclusive smaller areas, which are known as clusters. The use of an area frame with multistage sampling is very common and has the benefit of reduced travel costs (Gambino & do Nascimento Silva, 2009) and complete coverage of the targeted geographical area (Nusser & House, 2009). Given the benefits of the area sampling frame, this study employed the area sampling frame; that is, the geographical area of the Musanze district was considered an area frame and was divided into mutually exclusive sectors, i.e., clusters.

Once the frame was defined, the first stage of the two-stage clustering involved the random selection of mutually exclusive clusters from the frame. Although it is difficult to determine the right number of clusters, it is recommended to choose more clusters when possible rather than shooting for very few clusters hoping to get many respondents in each cluster. When designing studies, selecting more clusters increases the study's power more than selecting more elements in the clusters (Henderson & Sundaresan, 1982; Killip, Mahfoud, & Pearce, 2004). In this study, for example, rather than having 200 respondents in 3 sectors, the aim was to collect data from 80-90 respondents in 7 sectors. To fully represent the population of the Musanze district, we attempted to cover the four cardinal points – north, south, east, and west. Muhoza sector, which happens to be at the center of the district, was purposefully excluded. Since Muhoza is more urban than other sectors, and as such very few farming activities are conducted in that sector, it was less appropriate for collecting data on farmers' behaviors. From the Muhoza

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[3] pwr.f2.test(u=3, v=NULL, f2=0.02, sig.level = 0.05, power=0.8). N is deduced from v, the degree of freedom

[4] wp.regression(n=NULL,p1=8, p2=3,f2=0.02,alpha =0.05, power=0.8)

sector (excluded), we targeted farmers in the four cardinal points of the district[5]. The first sector to the right of the center was randomly chosen as the first sector (Gacaca). From Gacaca, we skipped one sector and chose the following one (Nyange, in this case). From Nyange we skipped another sector and then chose Shingiro. The same was done and then Busogo sector was chosen. To make it less systematic and more random, we chose the sector right next to Busogo (Nkotsi). Next, we skipped not one sector but two sectors towards the east and then chose Gashaki. At this point, we had six sectors. To increase representation, we purposefully added another sector (Kinigi) so we could include farmers who live close to the volcanoes. Ultimately, the study area (Figure 2.2) consisted of 7 sectors as our clusters: Busogo, Gacaca, Gashaki, Kinigi, Nkotsi, Nyange, and Shingiro.

The second stage of a two-stage cluster sampling typically consists of selecting units (elements) from the selected clusters (Galway et al., 2012; Hoshaw-Woodard, 2001), usually by simple random sampling (or often by systematic sampling) (Ahmed, 2009). Similarly, in this study, after the sectors (clusters) were selected, data were collected from randomly selected respondents in each cluster. Once in the selected sectors, a random household was picked to start with. Generally, a random spot along the main road or street would be picked and the data enumerators would go in four different directions. Every enumerator would pick a random house to start with, and then would skip a few houses and pick another household until someone to interview was found. This was not a systematic selection as it did not follow any consistent number of houses before picking the next; enumerators just walked a few meters and tried a few households until the person to interview was found. Ultimately, 604 responses were collected overall from the study area (Figure 2-2). This number is lower than the highest sample size estimate from power analysis (650) but is higher than the average (583) of the sample size estimates from various methods used during power analysis. Thus, it is a good estimate to work with and offers enough statistical power according to this study's power analysis.

[5] Even though Muhoza sector was purposefully avoided in the selection of clusters, data collected from the rest of the clusters fairly represent a typical farmer in Musanze district as a whole.

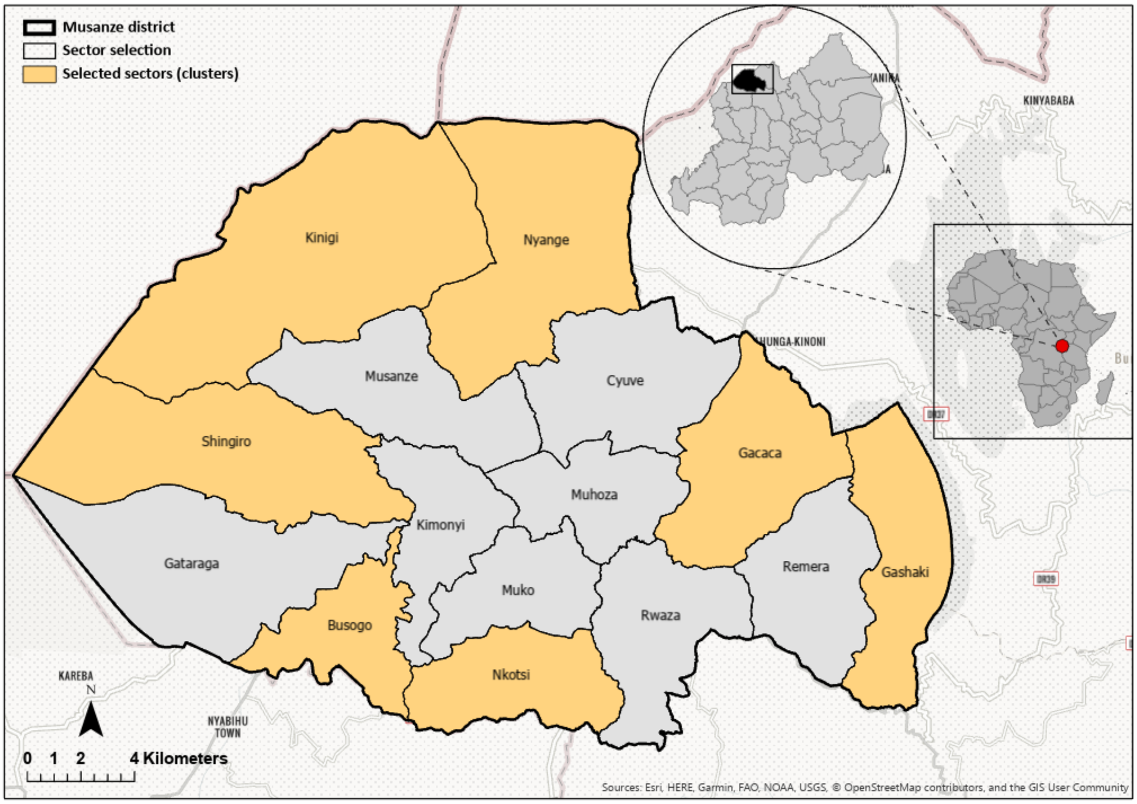

Figure 2-2: Study area, Musanze district, northern Rwanda

Instrumentation

Development of the instrument

This study used a structured interview to investigate environmental behaviors and their factors. The first step was to develop a questionnaire with items to capture both environmental behaviors and various related constructs. The questionnaire used in this study was adapted from the standard guide recommended by Fishbein & Ajzen (2010) in their book on Reasoned Action Approach (RAA) to understanding and predicting behavior (see its Appendix – Constructing a Reasoned Action Questionnaire, page 449) in addition to the questionnaires typically used in testing the Theory of Planned Behavior. Based on this guide, in developing the instrument, the behavior was first defined, and, then, items for direct measurement were formulated to assess each of the major constructs: attitude, perceived behavioral control, subjective norms, and intention. In the context of environmental behaviors, this type of measurement has been implemented in various studies such as studies by Fornara et al. (2011), Passafaro et al. (2019), Yaghoubi Farani et al., (2019), and de Leeuw et al. (2015).

Description of the instrument

To measure environmental behaviors, 6 Likert-type items were used (section C in the questionnaire) to examine how often or frequently respondents engaged in various environmental behaviors (example: "During the recent rainy month, how many times per week have you collected rainwater?"). Responses were rated on a 5-point scale ranging from 1 (None) to 5 (Seven days a week).

Apart from environmental behaviors, this study measured the central factor of behavior: behavioral intent; i.e., the intention to engage in environmental behaviors (Ajzen, 2012). Behavioral intent was measured by using 10 items (see G section in the questionnaire). Respondents were asked to answer pairs of questions for each environmental behavior. The first question in each pair was a binary (Yes/No) question about whether or not they were intending to engage in a given environmental behavior (sample item: "During the next rainy season, do you intend to harvest rainwater to increase water quantity in your household?"). Related to the first question, the second question of each pair was about the degree to which respondents were decided to engage in the chosen environmental behavior (sample item: "To what degree are you decided or undecided to harvest rainwater to increase water quantity in your household in the next rainy season?"). Responses options for the second question were rated on a 5-point Likert scale ranging from 1 (Very undecided) to 5 (Very decided).

Behavioral intent is a multidimensional measure of various aspects of behavior. Different studies indicated the existence of three main factors of intention: attitudes, subjective norms, and perceived behavioral control (Ajzen & Fishbein, 1977; Azjen, 1991; Fishbein & Ajzen, 1975; Madden et al., 1992). Following this logic, in addition to measuring intention, this study attempted to measure the three factors of behavioral intent. Thus, attitude measurements examined individuals' evaluation (favorable or unfavorable) towards the behavior to be performed whereas subjective norms examined perceived social pressure to engage in a given behavior. Lastly, perceived behavioral control dealt with people's perceptions of their ability to perform a given behavior.

To measure the first factor (attitudes), a total of 23 Likert-type items were used (see section D in the questionnaire). Respondents were asked to react to statements regarding their attitudes towards various resources such as charcoal, fertilizers (inorganic or organic), fuelwood, etc (sample item: "For me, harvesting rainwater is:" or "For me, using alternative sources of energy for cooking is:"). Responses were rated on 5-point scales ranging from 1 (Very bad) to 5 (Very good), 1 (Very wrong) to 5 (Very right), and 1 (Very useless) to 5 (Very useful).

To measure subjective norms, the second factor, 22 Likert-type items were used in total (see section E in the questionnaire). The first 3 items evaluated how neighbors, family members, and friends feel about certain environmental behaviors. That is, they evaluate to what degree this group of people approves or disapproves of the environmental behaviors. For instance, one question asked: *To what extent do your friends approve or disapprove of each of the following activities?* (The response options were *Harvesting rainwater, Using organic fertilizers*, and *Using alternative energy for cooking.* The following 3 questions were about ascertaining how important these groups of people are to the respondents (sample question: "How important are your neighbors to you?"). Responses were rated on a 5-point scale ranging from 1 (Very unimportant) to 5 (Very important). The rest of the questions included questions about descriptive norms (what is done) and injunctive norms (what should be done). For example, one question in the descriptive norms section asked to react to the following statement: *Most of my friends use organic fertilizer to increase their harvest.* Comparatively, in the injunctive norms section, one of the questions asked to react to the following statement*: Most of my neighbors think that I should harvest rainwater*. For both norms, the response options were rated on a 5-point scale ranging from 1 (Completely disagree) to 5 (Completely agree).

The third factor (perceived behavior control) was measured by using 3 Likert-type items (see section F in the questionnaire). Respondents were asked to reveal how easy or difficult it is for them to engage in a given environmental behavior based on proposed statements (sample item: "For me, using organic fertilizer to increase harvest would be:"). Response options were rated on a 5-point scale ranging from 1 (Very easy) to 5 (Very difficult).

Measurements that examine the constructs can only be useful if they are both reliable and valid. To ensure both the reliability and validity of the measures, this study performed certain tests. The reliability test is reported first in the following subsection.

Reliability

Reliability of a measure refers to the consistency of responses, which can be assessed by examining consistency across time, forms, individuals, or items (Huck, 2012; Kite & Whitley, 2018). Since this study used multiple items/questions, reliability across items, also known as internal consistency, was judged the most appropriate. This study employed the most commonly used internal consistency measure: the Cronbach Alpha coefficient (Cronbach, 1951); this is recommended when making use of Likert scales and multiple questions (Huck, 2012; Taherdoost, 2018), as was the case in this study. Although no absolute rules exist for internal consistencies, most agree on a minimum internal consistency coefficient of .70 (Kite & Whitley, 2018). As a guide, Hinton et al. (2004) proposed four cut-off points for reliability: excellent reliability (.90 and above), high reliability (.70 - .90), moderate reliability (.50 - .70), and low reliability (.50 and below). Too high a reliability could signal multicollinearity, thus it is crucial to bear that in mind while performing a reliability test (Abdrbo et al., 2011).

Although reliability is important, it is not sufficient unless it is combined with validity. In fact, for a test to be reliable, it also needs to be valid (Wilson, 2014). Thus, this study's validity tests are discussed next.

Validity

Apart from being reliable, a measure must also be valid. Validity of a measure refers to its degree of accuracy; that is, a valid measure assesses what it is intended to assess, assesses only what it is supposed to assess, and assesses all aspects of what it is supposed to assess (Kite & Whitley, 2018). One of the most common validity tests is content validity, which is concerned with the degree to which various items in a questionnaire collectively cover the material that the questionnaire is intended to cover (Huck, 2012). In general, the goal of conducting the content validity is to evaluate the instrument to ensure that it covers all the essential items and eliminate undesirable or unnecessary ones to particular constructs (Lewis et al., 1995; Taherdoost, 2018).

To establish the content validity of this study, an expert review was conducted. To do this, the questionnaire was sent to a panel of six professors who have research experience in human dimension research, rural sociology, applied economics, quantitative research, and international development. The panel members were asked to assess the instrument and its content before it was tested. Based on the comments of the panel members, the instrument was updated to reflect the changes suggested for clarity, relevance, structure, and organization of the instrument. Additional modifications were made to a few questions, mainly to improve the wording. The questionnaire was then tested (n=5) and piloted (n=8) in the field (see the data collection section below). In the test run, respondents were asked to further analyze the clarity, wording, and relevance of the questions. Although it is important to highlight the content validity to establish the validity of this study, it is often recommended to use more than one validity test (Huck, 2012). Thus, this study conducted another validity test: construct validity.

Construct validity refers to the evaluation of the extent to which a measure assesses the construct it is intended to measure (Strauss & Smith, 2009). It is regarded as the most important validity test as it deals with what the instrument is measuring (Lunenburg & Irby, 2008). To establish construct validity for various factors in this study (such as intention, attitudes, or subjective norms), factor analysis was performed. Factor analysis is used to assess whether it is likely that a certain group of observed items together measure a pre-specified unobservable construct (Civelek, 2018; Knekta et al., 2019).

Factor analysis

This study follows the Theory of Planned Behavior (TPB) and the Reasoned Action Approach (RAA) in running the factor analysis. Since this is a well-established theory, one can have an idea of the number of common factors as well as the measured variables that can be influenced by the same common factors. However, we added a few items to our questionnaire to better capture the constructs in the context of Rwandan farmers. This can have an impact on the number of factors. Additionally, one cannot be sure that these newly added items will be affected only by the factor of interest and not by related factors in that domain. When additional items are added to an established theory, the recommendation is to perform an Exploratory Factor Analysis (EFA), with the proviso to conduct a Confirmatory Factor Analysis (CFA) later (Leandre & Wegener, 2011). The present study followed that recommendation. Before running the factor analysis, the study proceeded with assessing the factorability of the data as the first step as recommended by the procedure using both the Kaiser-Meyer-Olkin (KMO) factor adequacy test and Bartlett’s test for sphericity (Dziuban & Shirkey, 1974; Kaiser, 1974); while the former assesses whether there is at least one latent variable among the data, the latter evaluates whether there is an intercorrelation among the variables at all.

EFA involved (1) preparing data, (2) determining the number of factors, and (3) running the analysis. As recommended by Leandre and Wegener (2011), once the EFA is run and the common factors determined, it is worth confirming results from EFA by running CFA. The goal of running CFA was to confirm the hypothesized number of constructs (obtained from EFA), the relationship between the constructs, and the relationship between the constructs and the items. Both EFA and CFA were run using the R (R Core Team, 2013), a software for statistical programming. For CFA, model fit indices were used to assess model fit; these include the comparative fit index (CFI), the root-mean-square error of approximation (RMSEA); and the standardized root-mean-square residual (SRMR).

Missing values treatment

Treating missing values constitutes a crucial step in any research endeavor. Although most standard statistical methods presume a complete dataset, the reality is that most datasets are not complete (Allison, 2002; Kang, 2013). This can result in less statistical power, biased estimates, and, potentially, invalid conclusions (Kang, 2013). This study was no exception; some questions were not answered, thus resulting in an incomplete data set. To avert these challenges arising from incomplete datasets, missing values should be appropriately treated. There are many ways to treat missing values. The default treatment is often listwise deletion; i.e., deleting any case that has missing values. Though quick and simple, this approach results in a dataset with much less information and smaller sample size – thus, less power – than the original dataset (Allison, 2002). Different methods have been developed to offer improvements over listwise deletion. The two most common methods[6] are Maximum Likelihood (ML) and Multiple Imputation (MI) (Allison, 2002; Bosma & Witteloostuijn, 2021). Although both methods perform better than listwise deletion, MI seems to be a better missing data treatment, especially at the stage of theory building such as factor analysis[7] (Bosma & Witteloostuijn, 2021; Nassiri et al., 2018). The present study, thus, employed MI to deal with missing values. This was implemented by using the R (R Core Team, 2013) package called mice (Multiple Imputation by Chained Equations) developed by van Buuren and Groothuis-Oudshoorn (2011).

Ethical approval

Data collection was conducted with ethical considerations and was approved by the Internal Review Board (IRB) at the University of Tennessee, Knoxville (IRB number: UTK IRB-21-06216-XM IRB). To obtain the approval letter, several documents were submitted to IRB; these include an informed consent form, an alternative[8] training material used to train enumerators, an

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[6] There exist other methods, such as Single Imputation (SI) and Pairwise deleting (Allison, 2002; Bosma & Witteloostuijn, 2021), Mean substitution, Regression imputation, Last observation carried forward, expectation-maximization, Sensitivity analysis (Kang, 2013).

[7] For more information about technical details on using Multiple Imputation on incomplete data in factor analysis, see (Nassiri et al., 2018). For technical details about Multiple Imputation in general, see (Rubin, 2004) and (Carpenter & Kenward, 2013)

[8] The alternative training was used so that enumerators did not have to complete the online CITI training as that could have posed a challenge to do. Alternatively, a training module was developed and adapted from an alternative CITI training compiled by a UTIA research team that

individual investigator agreement, and a cultural appropriateness letter from the local authorities in Rwanda where the study was conducted. The approval letter was obtained on June 23rd, 2021, after which time did data collection start.

Data collection

To conduct a smooth data collection, a pre-test and a pilot were first conducted to ensure that the questions were clearly articulated and to identify potential problems throughout the entire survey.

The pre-test was conducted on July 7th of 2021 and consisted of asking people (N=4) the survey questions to determine whether or not the questions were relevant and comprehensive from the respondent's point of view – not that of the researcher. Additionally, pre-testing helped to gauge the response latency, which is the amount of time it takes to complete individual items on the survey as well as the full survey (Mulligan et al., 2003). The pre-test used in this study was the respondent-driven pre-test (as opposed to the expert-driven pre-test). The respondent-driven pre-test can be targeted to either colleagues and friends or a small sample of the target population. The pre-test of this study targeted colleagues and friends, particularly the enumerators who were going to administer the survey.

Both behavior coding and cognitive interview were used to collect data during the pre-test. In the behavior coding, the behaviors of respondents were recorded and noted as they went through the questions, especially those that might indicate potential problems and difficulty in responding to some of the questions. These problems may include confusion, hesitation, or frustration. By contrast, in the cognitive interview, the pretest respondents were encouraged to think out loud and voice their ongoing mental reactions to questions while responding. The objective was to collect their thought processes as they responded to questions as this might improve the survey by avoiding confusion in the questions.

In addition to the pretest, a pilot study was conducted to identify potential problems throughout the entire survey. The pilot study was conducted on July 10th, 2021 on a sample of 8 respondents from the study area. The pilot helped in assessing whether the research project was feasible, realistic, and rational from start to finish. Additionally, the pilot test aided in determining whether the enumerators were well trained, and understood the questions well, which turned out to be the case.

Some adjustments were made to the questionnaire after the pre-test and the pilot to reflect some of the suggestions that surfaced during the feedback on the pre-test run and the pilot. For example, one question (question G9 in the questionnaire) was edited to reflect the timeframe change. The question was: "*During the next month, do you intend to use organic fertilizer to increase your harvest?*" As it turned out, this question was unclear to most respondents during pre-test and pilot runs. The confusion was that one, for instance, could very well intend on using organic fertilizer (or any other environmental behavior) in the coming months but not necessarily the next month. In this case, we had to change the timeframe to three months. The alternative

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did a research in Rwanda and approved by UTK IRB in 2017. The training module was submitted as part of the IRB application for this study and was approved.

could have been six months but the challenge would have been the difficulty to gauge to what extent they were decided to act on that behavior if the timeframe was that long (which was the next question in that section). Thus, we used three months as a fixed timeframe. The new question was: *"In the next three months, do you intend to use organic fertilizer to increase your harvest?"* Another adjustment made to the questionnaire was on one of the behavior questions (question B3). The question asked: "*Which of the following activities of water conservation do you use in your household?"* The response options were multiple but it was later decided that the responses be binary (Yes/No) on each response option as this helped avoid confusion in responding to the question and is likely to avert the difficulty in analyzing data with multiple responses.

After the pretest and the pilot, data were collected by administering a survey to randomly selected farmers in the Musanze district between July and August of 2021. The questions were loaded into the iSurvey (version 2.14.32) and DroidSurvey (version 2.9.3) software, two versions of the same data collection tool operated by HarvestYourData[9], a mobile survey software. Using these tools, data were collected offline during the day and were uploaded onto the HarvestYourData database at the end of each day of data collection. In total, 4 devices (3 iPads and 1 tablet) were used to collect data.

During data collection, respondents were first asked if they were willing to accept to participate in the survey; this was achieved by using the recruitment script – only when they accepted did the data collection proceed. Once they accepted to participate, they were read the informed consent document so that they were aware of what their participation entailed (risks, benefits, or confidentiality). Participants were asked to respond to a set of questions to which they were expected to answer. However, according to the consent form, they were welcome to skip any questions they felt they did not want to answer or stop the survey altogether whenever they deemed it necessary.

The questionnaire had 8 sections of questions, each with its theme: (1) screening questions, (2) natural resources management, (3) environmental behaviors, (4) attitudes, (5) subjective norms, (6) perceived behavioral control, (7) intention, and (8) socioeconomics. In addition to these questions, geographical location data (latitude and longitude) were gathered for spatial data analysis. To do that, this study used the Global Positioning System (GPS) and location services embedded in the iPads and Tablets used during data collection. On average, each survey took between 15 and 20 minutes to complete. After the survey, each participant was thanked for their participation and was asked if they had any comments or questions they had before closing.

Data analysis

Descriptive statistics

Descriptive statistics were used to describe the basic features of the data. They provided summaries of the sample and the measures of the collected data. This included both summary tables and graphics showing various aspects of the collected data.

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[9] Address for the HarvestYourData: www.harvestyourdata.com; address: 3 Kaitawa Road York Bay Lower Hutt New Zealand

Structural Equations Model

To analyze the collected data, the Structural Equation Modeling (SEM) technique was applied. SEM is a statistical modeling method used to measure relationships between observed variables and latent variables. While observed variables can be measured directly from data collected in the study, latent variables cannot (Civelek, 2018). Latent variables are variables or factors that are important to the model but for which we do not have the data. They are known as unmeasured or unobserved variables (Bollen, 2002).

In studying relationships among the given variables, there are two main reasons to use SEM instead of other statistical methods. The first reason is that SEM allows to model relationships between observed variables and latent variables (Hox & Bechger, 2015). Unlike multiple regression analysis, SEM can capture the relationships between latent, unobserved variables (e.g., environmental behaviors, intentions, perceived behavioral control, subjective norms, or attitudes) and observed variables (i.e. gender, income, age) because it was designed to capture these subtle relationships between unobserved and observed variables (Alavifar et al., 2012; Gray, 2019)

The second reason to use SEM – and one of the features that sets it apart – is its ability to capture the dependence relationships between dependent variables and independent variables. This dependence is expressed when in some cases a dependent variable can become an independent variable, thus creating an interdependence of the structural model. While traditional modeling techniques fail to capture these dependence relationships, SEM excels at capturing them. SEM achieves this by translating these relationships into a series of separate interdependent structural equations for every dependent variable, unlike other methods – such as factor analysis – that only cater for only one relationship between a dependent variable and an independent variable (Hair et al., 2014).

The SEM has two main components: a measurement model and a structural model. The measurement model establishes the relationship between latent variables and observed variables while the structural model examines the relationships between latent variables. Eq. 1 and Eq. 2 illustrate the measurement models for the endogenous and exogenous variables, respectively. Endogenous variables are dependent variables that are explained by other variables whereas exogenous variables are independent variables that are not explained by any other variables. This distinction is important because in SEM, a variable can be both a dependent and independent variable at the same time (Civelek, 2018).

$$y = \Lambda_y \eta + \varepsilon \quad (1)$$
$$x = \Lambda_x \xi + \delta \quad (2)$$

where *y* represents a p x 1 vector of endogenous observed variables whereas *x* represents a q x 1 vector of exogenous observed variables. η is an m x 1 vector of latent endogenous variables and ξ is an n x 1 vector of latent exogenous variables. Λ_y and Λ_x represent p x m and q x n matrices of loadings (or coefficients). Lastly, ε and δ are p x 1 and q x 1 vectors of measurement errors of *y* and *x*, respectively.

The structural model is illustrated in Eq. 3:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (3)$$

where η and ξ are defined in eq. 1 and eq. 2. B represents an m x m matrix of coefficients (β_{ij}) reflecting the effect of the jth endogenous latent variable on the ith endogenous latent variable. Γ is an m x n matrix of coefficients (Υ_{ij}) reflecting the effect of the jth exogenous latent variable on the ith endogenous latent variable. Lastly, ζ represents an m x m vector of disturbances.

The SEM approach in this study involved the following steps: specification, identification, model estimation, model evaluation, respecification, and results reporting. The specification step was useful in representing the hypotheses of the study. For example, the model in the present study specified behavioral intention as being influenced by attitudes, norms, perceived behavior control, and background factors (age, income, and others). Identification was run through the CFA stage to ensure that the software could derive unique estimates for every model parameter. Moreover, all the models were estimated using the maximum likelihood estimator, which is by far the most commonly used estimator in SEM and a default estimator in most software packages (Civelek, 2018; Kline, 2011). The models were assessed to evaluate their fit. Model fit indices were used to accomplish this task; these indices include the comparative fit index (CFI), the root-mean-square error of approximation (RMSEA); and the standardized root-mean-square residual (SRMR). The present study used the fit measures recommended by Hu and Bentler (1999) to determine model fit: RMSEA <0.06; CFI>0.95; SRMR<0.08.

To implement the SEM technique in this study, the Latent Variable Analysis (Lavaan) package was used. Lavaan is an R (R Core Team, 2013) package that was designed by Rosseel (2012) specifically to model latent variables using the SEM approach. This method has been used in other studies to understand the environmental behaviors and intentions of farmers (Dang et al., 2014; Luu et al., 2019).

Results

Descriptive statistics

Socioeconomic variables

Sociodemographic information collected in this study included age, gender, land ownership and size, income categories, marital status, and school attendance. The mean age was 45 years of age (SD=14). Further, results (Table 2-1) indicate that data were collected from more male respondents (54%) than their female counterparts. While the majority reported owning land, the land size was largely below 1ha. Most respondents reported that they earn less than RWF 50,000 (~$50 as of August 2021). Regarding education, 17% completed primary school whereas 16% completed high school. Only 4% completed university (further results on education are summarized in Table 2-8 of the appendix 2.1).

Natural resources management variables

Water conservation: Data indicate that very few respondents (10%) have running water in their households; those who don't have running water in their household (90%) live within 10 minutes of walking distance to the closest main source of water. Data further indicate that respondents are involved in some water conservation practices. For instance, 92% of respondents reported that they harvest rainwater, over 95% reduce the water they use in different household activities, and 84% reuse water.

Table 2-1: Summary statistics for socio-demographic information among farmers in Musanze district, 2019

Variable	Categories	Frequency	Percentage
Gender	Male	321	53.77
	Female	276	46.23
Land	Yes	560	93.96
	No	36	6.04
Land size	Less than 1 ha	513	91.61
	Between 1ha and 5 ha	47	8.39
Income	Below RWF 50,000	432	72.85
	Between RWF 50,000 and RWF 100,000	149	25.13
	Between RWF 100,000 and RWF 500,000	12	2.02
Marital status	Married	494	85.91
	Widowed	81	14.09
School attendance	Completed 6 years of primary	67	17.31
	Completed secondary	56	15.91
	Completed university	7	3.66

Sources of energy for domestic cooking: The majority of respondents reported that they never use charcoal, pellets, gas (LPG), electricity, or biogas for domestic cooking. Instead, they primarily use fuelwood as the main source of energy. Around 82% reported that they use fuelwood very frequently. Around 80% of respondents reported that they use a traditional cooking setup (three rocks). This indicates that they use fuelwood as the source of energy for cooking. Comparatively, only 15% reported that they use a regular cooking stove, thus suggesting that they use charcoal as the main source of energy source for domestic cooking.

Fertilizer use: Around 96% of respondents reported that they use fertilizer to increase their agricultural production. Of those who use fertilizer, 12% use organic fertilizer only whereas 2% use inorganic fertilizer only. However, the majority of respondents (86%) reported that they use both inorganic and organic fertilizers.

Environmental behaviors variables

Farmers engage in environmental behaviors differently depending on the type of resources. Results (Table 2-2) revealed that respondents use improved cooking stoves occasionally but rarely use pellets, biogas, or LPG gas for domestic cooking. Further, the environmental behaviors in which farmers engage more frequently are rainwater collection and organic fertilizer use.

Factors of environmental behaviors

Attitudes**:** Overall, the attitude towards selected behaviors was positive; that is, the majority of respondents reported that these behaviors were good, right, or useful (Table 2-9). Although the common attitude was positive for most behaviors, that was not the case when respondents were asked how expensive or inexpensive various behaviors were. For example, while some respondents felt that using organic fertilizer was expensive (56%), others (31%) felt that it was inexpensive. These mixed reactions were also found in the case of the use of alternative sources of energy, the use of charcoal, and the use of fuelwood.

Subjective norms: Regarding subjective norms, i.e., perceived social pressure to engage in a given behavior, respondents reported that all groups (neighbors, family members, and friends) approved of all environmental behaviors (rainwater harvesting, the use of organic fertilizer, and the use of alternative sources of energy) (Table 2-10, section A - appendix).

Descriptive norms: while respondents thought that their neighbors, family members, and their friends were engaged in environmental behaviors such as rainwater harvesting and the use of organic fertilizer, they did not think these groups were using alternative sources of energy (Table 2-10, section B - appendix).

Table 2-2: Responses on how frequent farmers engage in different environmental behaviors in Musanze District, Rwanda, 2021

		1	**2**	**3**	**4**	**5**
Description	n	*None* (%)	*One to two days a week* (%)	*Three to four days a week* (%)	*Five to six days a week* (%)	*Seven days a week* (%)
Rainwater harvesting	553	13.38	21.16	26.22	0.00	39.24
Improved cooking stoves	591	69.88	12.01	12.52	0.00	5.58
Pellets	595	99.50	0.17	0.17	0.00	0.17
Biogas	591	99.15	0.51	0.00	0.00	0.34
LPG (gas)	594	97.64	0.67	1.35	0.00	0.34
		1	**2**	**3**	**4**	**5**
		Never (%)	Rarely (%)	Sometimes (%)	Frequently (%)	Very frequently (%)
Organic fertilizer	595	5.55	3.36	10.92	32.61	47.56

***Injunctive norms*:** The same sentiment was revealed with injunctive norms. That is, overall, even though their neighbors, family members, and friends think respondents should engage in rainwater harvesting and the use of organic fertilizer, they (respondents) did not feel that these groups think respondents should use alternative sources of energy (Table 2-10, section C - appendix).

Results from subjective norms can depend on how respondents value different groups (neighbors, family members, or friends). That is, the importance that respondents ascribe to these groups is crucial as it may determine how they respond to the subjective norm questions. Thus, the study examined the importance that respondents assign to different groups. The study's results indicate that overall respondents found the neighbors, family members, and friends important or very important (Table 2-11 - appendix).

Perceived behavior control: The study examined respondents' perceptions of their ability to engage in different environmental behaviors, i.e., their perceived behavior control. Results on perceived behavior control (Table 2-3) indicate that respondents' perception of their ability varied with the type of behavior. For instance, most respondents (77%) thought rainwater harvesting would be easy. Likewise, a little over half of the respondents thought using organic fertilizer would be easy. In contrast, half of the respondents thought using alternative sources of energy would be difficult.

***Intention*:** As the key factor in TPB, behavioral intent is the basis for an individual's motivation to perform a given action. This study assessed respondents' intention to engage in various environmental behaviors. Results (Table 2-12 - in appendix) reveal that, overall, respondents have the intention to harvest rainwater and use organic fertilizer. However, the same was not true for the use of alternative sources of energy; most respondents reported they were intending to use pellets, improved cooking stoves, or LPG gas.

Having intention is one thing; being decided on the intention is another altogether. Literature suggests that the stronger the intention to engage in a given behavior, the more likely to engage in that behavior. Thus, in addition to assessing intentions, this study further examined the degree to which respondents were decided or undecided to engage in the given behaviors. Results (Table 2-12 – in appendix) indicate that, overall, the majority of respondents are decided on their intentions regarding rainwater harvesting and the use of organic fertilizer.

Table 2-3: Summary responses (%) of respondents' perceived behavior control in Musanze district, Rwanda, 2021

	Rainwater *(%)*	**Alternative energy** *(%)*	**Organic fertilizer** *(%)*
	For me, harvesting rainwater to increase water quantity in the household would be	*For me, using alternative sources of energy for cooking would be*	*For me, using organic fertilizer to increase harvest would be*
1: Very easy	9.60	0.34	5.05
2: Easy	77.10	8.91	51.68
3: Neither easy nor difficult	2.69	5.04	18.86
4: Difficult	8.08	50.92	12.79
5: Very difficult	2.53	34.79	11.62
	n=594	*n=595*	*n=594*

Results from factor analysis

Validity: To ascertain the factorability of the data, two tests were run: Bartlett’s test for sphericity and the Kaiser-Meyer-Olkin (KMO) test. Bartlett’s sphericity test was statistically significant ($p<.001$), thus suggesting that there was a difference between an identity matrix and the observed matrix. This implies that there is some correlation among the data. This test was complemented with the sampling adequacy measure (KMO), which determines whether there is at least one factor among data. Results of the KMO test indicated that the overall Measure of Sampling Adequacy (MSA) of the test was .84. This measure was deemed an appropriate measure as the recommended value is 0.5 or above (Hair et al., 2014). The results from both tests (Bartlett’s and KMO) indicated that data were factorable and that factor analysis could be performed.

Exploratory Factor Analysis (EFA): The first decision to make in factor analysis was to determine the number of factors to extract from the data. This could be done in different ways, but this study used both the scree plot and the parallel analysis scree plot (see an example of a scree plot for the “attitude” subscale in Figure 2-3). Using these plots, the number of factors to extract was determined for multiple-item subscales; these include the attitude subscale and subjective norm subscale. Based on this method the attitude subscale had 7 factors whereas the subjective norm subscale had 6 factors.

In performing factor analysis, the assumption was that the variables were independent; thus, the orthogonal rotation (varimax) was used on all item subscales. The loadings matrix was generated to identify the factors and the variables that loaded on the identified factors. For example, after an orthogonal rotation, factor analysis categorized the attitude items under (Factor 1) attitude towards expensiveness or inexpensiveness of a given behavior, (Factor 2) attitude towards rainwater harvesting, (Factor 3) attitude towards alternative sources of energy, (Factor 4) attitude towards the use of inorganic fertilizer, (Factor 5) attitude towards the use of organic fertilizer, (Factor 6) attitude towards the use of charcoal, and finally (Factor 7) attitude towards the use of fuelwood (Table 2-13 - in appendix).

The factor analysis results for the norms subscale indicated that variables loaded on six factors as follows: descriptive and injunctive norms were categorized under three different factors based on (Factor 1) alternative sources of energy, (Factor 2) rainwater harvesting, and (Factor 3) the use of organic fertilizer. Furthermore, subjective norms formed three distinct factors based on (Factor 4) alternative sources of energy, (Factor 5) rainwater harvesting, and (Factor 6) the use of organic fertilizer (Table 2-14 - in appendix).

The intention subscale formed one factor based on the degree of the intention of undertaking a given behavior.

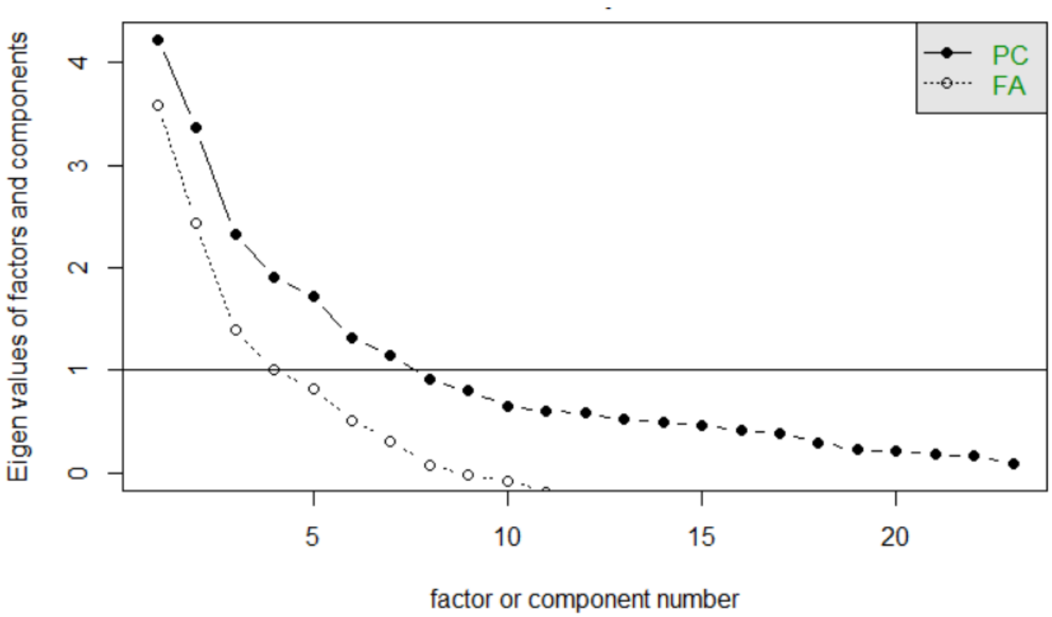

Figure 2-3: The use of a scree plot to determine the appropriate number of factors to extract from the "attitude" subscale in the data set. Data collected from farmers (n=604) in Musanze district, Rwanda 2021

Reliability: According to Hinton et al. (2004)'s guide, the attitude subscale, the subjective norms subscale, and the behavioral intent had high reliability. In contrast, the environmental behaviors subscale had low reliability (Table 2-15 in appendix). As for behavior, it was decided to use behavioral intent for further analysis since it had higher reliability.

It is worth noting that the subjective norms factor was separated from those of descriptive and injunctive norms as this distinction seemed to yield more robust confirmatory test results. Following Farrow et al. (2017)'s classification, descriptive and injunctive norms can be grouped into social norms or simply norms. The distinction between norms is an important one in studying their effect on behavioral intention. Particularly, the distinction between descriptive and injunctive is important as they can be shown to affect individual behaviors differently, and they can be tied to different sources of motivation. For example, injunctive norms may motivate an individual to act simply because he or she desires social approval. Comparatively, descriptive norms may motivate one to act because he or she is capable of discerning what is deemed to be the more appropriate behavior option (Cialdini et al., 1990; Fornara et al., 2011). This distinction is further supported by Niemiec et al. (2020)'s analysis that observed that the impact of norms on behavior may vary depending on the type of norms.

Confirmatory Factor Analysis (CFA): based on the results from the exploratory phase of factor analysis, three models were run in the confirmatory factor analysis (CFA): the model on rainwater harvesting, the model on organic fertilizer, and the model on alternative sources of energy. Overall, the CFA results revealed that the one-factor model for each subscale was the best fit (Table 2-4), confirming that each subscale was unidimensional; that is, a set of items for every subscale measures only one underlying construct. Figures 2-4, 2-5, and 2-6 illustrate the three models.

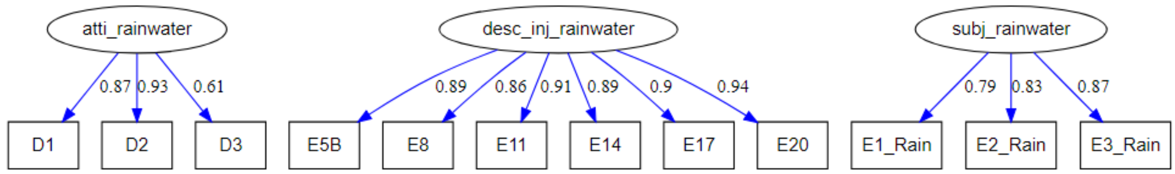

Figure 2-4: Confirmatory Factor Analysis of the rainwater harvesting among farmers (n=604) in the Musanze district, Rwanda (2021)

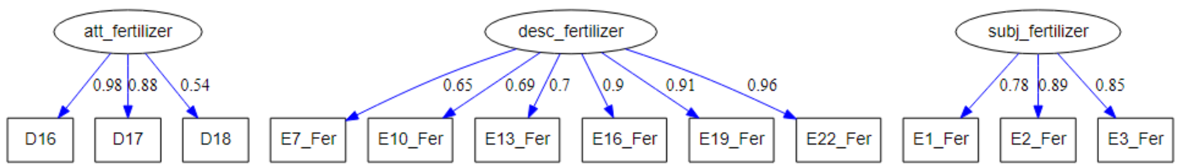

Figure 2-5: Confirmatory Factor Analysis of (organic) fertilizer use among farmers (n=604) in the Musanze district, Rwanda (2021)

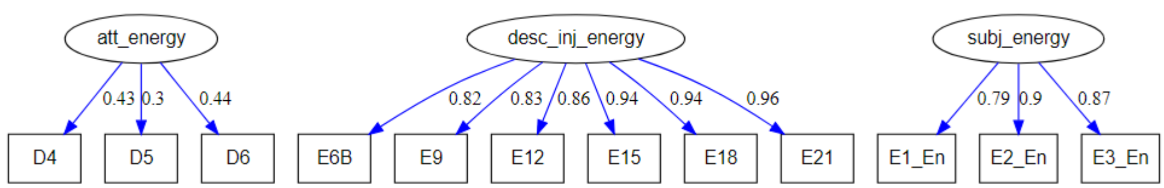

Figure 2-6: Confirmatory Factor Analysis of the use of alternative sources of energy for domestic cooking among farmers (n=604) in the Musanze district, Rwanda (2021)

Table 2-4: Goodness-of-fit indices for three confirmatory factor analysis (CFA) models: Rainwater harvesting, Organic fertilizer, and Alternative sources of energy)

No.	Model	Index	Proposed	Recommended*
1	Rainwater harvesting	RMSEA	0.085	< 0.06
		CFI	0.965	> 0.95
		SRMR	0.028	< 0.08
2	Organic fertilizer	RMSEA	0.063	< 0.06
		CFI	0.980	> 0.95
		SRMR	0.047	< 0.08
3	Alternative sources of energy	RMSEA	0.085	< 0.06
		CFI	0.968	> 0.95
		SRMR	0.076	< 0.08

**According to Hu and Bentler (1999)*

Results from SEM analysis

Once the model was confirmed through the confirmatory factor analysis, the next step was to fit the model with the SEM model to include regressions featuring both latent and manifest variables. Three SEM models were run to fit the data. Different iterations were run and only the best-fitting models were preferred after all possible improvements as evidenced by the goodness-of-fit assessment results. Models were improved using modification indices to increase the likelihood of picking the best-fitting possible model.

Behavioral intent was treated as an indicator of an environmental behavior; this consideration is driven by the idea that an environmentally significant behavior is determined by the motivation to act (Poortinga et al., 2004). Other studies modeled structural equations based on the intention to undertake a given environmental behavior (instead of the actual behavior); these include Fornara et al. (2011) who used the structural equation model to predict recycling intentions. Results from the analysis were standardized; thus, the magnitude of the effects is not relevant. The significance and the sign of the effects provide essential information.

Rainwater harvesting model: Results from the rainwater model (Table 2-5) show that attitude towards rainwater harvesting was found to have a significant and negative effect on behavioral intention ($p<.001$). Likewise, descriptive and injunctive norms had a significant effect ($p<.001$) but their effect was positive. Like the descriptive and injunctive norms, subjective norms had a significant – though, negative – effect ($p<.05$) on behavioral intent. In contrast to attitude and norms, perceived behavior control did not prove to have any effect on behavioral intent.

Fertilizer model: Results of the fertilizer model (Table 2-6) indicate that attitude towards the use of organic fertilizer has a significant and positive effect on behavioral intent. Although descriptive and injunctive norms proved significant and positive, subjective norms did not have any effect on behavioral intent. Perceived behavior control of using organic fertilizer proved to be non-significant.

Alternative sources of energy for domestic cooking: Regression results from the energy model (Table 2-7) indicated that attitude did not have a significant effect on the intention to undertake alternative sources of energy for domestic cooking. While both the descriptive and injunctive factors of norms proved to have a negative and significant effect on behavioral intent (both at $p<.001$), the subjective factor, in contrast, did not have a significant effect. Perceived behavior control proved to have a negative and significant effect on intention ($p< .001$).

Table 2-5: Regression results from the SEM analysis for the “Rainwater harvesting” model

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Intention - Rainwater	~					
Attitude	-0.094	0.029	-3.311	0.001**	-0.097	-0.154
desc_inj	0.243	0.029	8.456	0.000***	0.247	0.391
subj	-0.052	0.026	-2.001	0.045*	-0.053	-0.085
PBC	-0.005	0.029	-0.176	0.860	-0.005	-0.007
att_rainwater	~					
Age	0.000	0.003	-0.128	0.898	0.000	-0.006
marital	0.086	0.072	1.187	0.235	0.083	0.059
income	-0.106	0.089	-1.189	0.234	-0.103	-0.052
Land	0.472	0.185	2.552	0.011*	0.459	0.110
school	0.676	0.176	3.849	0.000***	0.658	0.174
gender	-0.139	0.094	-1.481	0.139	-0.135	-0.067
desc_inj_rainwater	~					
Age	-0.001	0.003	-0.386	0.699	-0.001	-0.018
marital	-0.006	0.070	-0.093	0.926	-0.006	-0.004
income	-0.204	0.085	-2.403	0.016*	-0.201	-0.100
Land	0.454	0.180	2.526	0.012	0.448	0.107
school	0.281	0.170	1.660	0.097	0.277	0.073
gender	0.152	0.091	1.673	0.094	0.150	0.075
subj_rainwater	~					
Age	0.006	0.003	1.795	0.073	0.006	0.087
marital	-0.027	0.073	-0.375	0.707	-0.027	-0.019
income	0.051	0.089	0.578	0.563	0.050	0.025
Land	0.383	0.189	2.020	0.043*	0.377	0.090
school	0.497	0.178	2.783	0.005**	0.489	0.129
gender	0.073	0.095	0.773	0.440	0.072	0.036
PBC	~					
age	0.005	0.003	1.709	0.087	0.005	0.078
marital	-0.010	0.056	-0.180	0.857	-0.010	-0.009
income	-0.086	0.068	-1.275	0.202	-0.086	-0.052
land	0.014	0.143	0.099	0.921	0.014	0.004
school	-0.318	0.135	-2.355	0.019*	-0.318	-0.102
gender	-0.004	0.072	-0.058	0.954	-0.004	-0.003

$*p < .05$; $**p < .01$; $***p < .001$

Table 2-6: Regression results from the SEM analysis for the "Fertilizer" model

Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all	
Intention - Fertilizer	~					
att_fertilizer	0.098	0.027	3.707	0.000***	0.103	0.173
desc_fertilizr	0.140	0.026	5.355	0.000***	0.153	0.256
subj_fertilizr	-0.003	0.025	-0.117	0.907	-0.003	-0.005
PBC	0.041	0.021	1.901	0.057	0.041	0.076
att_fertilizer	~					
Age	0.003	0.003	0.847	0.397	0.003	0.038
marital	-0.077	0.07	-1.105	0.269	-0.074	-0.052
income	-0.232	0.09	-2.562	0.010**	-0.221	-0.11
Land	0.924	0.183	5.046	0.000***	0.882	0.21
land_size	0.153	0.159	0.959	0.338	0.146	0.041
school	0.075	0.171	0.437	0.662	0.071	0.019
gender	-0.303	0.092	-3.291	0.001**	-0.289	-0.144
desc_fertilizer	~					
age	-0.004	0.003	-1.259	0.208	-0.004	-0.055
marital	0.074	0.07	1.054	0.292	0.068	0.048
income	-0.265	0.091	-2.911	0.004**	-0.243	-0.121
land	1.124	0.185	6.088	0.000***	1.032	0.246
land_size	0.352	0.16	2.2	0.028*	0.324	0.091
school	0.574	0.172	3.336	0.001**	0.527	0.139
gender	-0.449	0.093	-4.851	0.000***	-0.412	-0.205
subj_fertilizer	~					
age	0.006	0.003	1.677	0.094	0.006	0.081
marital	-0.089	0.073	-1.226	0.220	-0.088	-0.062
income	0.195	0.094	2.068	0.039*	0.191	0.095
land	0.308	0.189	1.631	0.103	0.302	0.072
land_size	-0.097	0.166	-0.584	0.559	-0.095	-0.027
school	0.248	0.177	1.395	0.163	0.243	0.064
gender	-0.121	0.095	-1.278	0.201	-0.119	-0.059
PBC	~					
age	0.007	0.004	1.869	0.062	0.007	0.084
marital	-0.029	0.074	-0.395	0.693	-0.029	-0.019
income	-0.142	0.096	-1.477	0.140	-0.142	-0.063
land	0.134	0.192	0.699	0.485	0.134	0.029
land_size	-0.543	0.169	-3.207	0.001**	-0.543	-0.137
school	-0.081	0.181	-0.447	0.655	-0.081	-0.019
gender	0.295	0.097	3.044	0.002**	0.295	0.132

$*p < .05$; $**p < .01$; $***p < .001$

Table 2-7: Regression results from the SEM analysis for the "Alternative sources of energy" model

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Intention - Energy	~					
att_energy	0.000	0.052	-0.006	0.995	0.000	0.000
desc_inj_enrgy	-1.516	0.096	-15.759	0.000***	-0.836	-0.836
subj_energy	0.014	0.051	0.265	0.791	0.007	0.007
PBC	-0.360	0.057	-6.314	0.000***	-0.200	-0.200
att_energy	~					
age	-0.017	0.008	-2.073	0.038*	-0.013	-0.181
marital	-0.552	0.185	-2.990	0.003**	-0.411	-0.291
income	-0.237	0.202	-1.174	0.240	-0.176	-0.088
land	0.390	0.411	0.950	0.342	0.291	0.069
school	-0.065	0.406	-0.160	0.873	-0.048	-0.013
gender	-1.207	0.300	-4.020	0.000***	-0.899	-0.448
subj_energy	~					
age	0.003	0.003	0.756	0.450	0.003	0.036
marital	-0.006	0.072	-0.082	0.934	-0.006	-0.004
income	0.001	0.088	0.007	0.994	0.001	0.000
land	-0.346	0.186	-1.858	0.063	-0.341	-0.081
school	0.542	0.176	3.075	0.002**	0.534	0.141
gender	-0.122	0.094	-1.291	0.197	-0.120	-0.060
desc_inj_energy	~					
age	-0.002	0.003	-0.534	0.593	-0.002	-0.024
marital	0.191	0.070	2.727	0.006**	0.183	0.130
income	0.264	0.085	3.100	0.002**	0.254	0.126
land	0.003	0.179	0.015	0.988	0.003	0.001
school	0.509	0.170	2.993	0.003**	0.489	0.129
gender	-0.425	0.092	-4.634	0.000***	-0.409	-0.204
PBC	~					
age	0.006	0.003	2.000	0.046*	0.006	0.088
marital	-0.166	0.069	-2.424	0.015*	-0.159	-0.112
income	-0.517	0.084	-6.117	0.000***	-0.494	-0.246
land	0.187	0.176	1.059	0.289	0.178	0.043
school	-0.042	0.166	-0.250	0.803	-0.040	-0.011
gender	0.342	0.090	3.809	0.000***	0.327	0.163

**p < .05; **p < .01; ***p < .001*

Discussion

Overall, behavioral intent to engage in an environmental behavior was found to be influenced by attitude, subjective norms, and perceived behavior control – as hypothesized by the Theory of Planned Behavior (TPB.) However, as revealed by the three models run in this study, both the significance of the influence and the direction of the influence of these factors on behavioral intent may vary based on the environmental behavior considered.

Attitudes: Attitude was found to have a significant effect on rainwater harvesting and the use of fertilizer. This finding accords with previous studies that found a significant relationship between attitude and environmental behavior – see Farani et al. (2019); Chen (2016); and Dijk et al. (2016) – thus, suggesting the importance of attitude in determining behavioral intention or actual behavior. The direction of the influence was not the same across behaviors, however. In the case of rainwater, the influence was negative whereas it was positive in the case of the use of fertilizer. The negative influence of attitude on rainwater harvesting suggests that the more farmers perceive rainwater harvesting as a good, useful, and right practice, the less decided they are to harvest rainwater as a means to increase the water quantity in their household. In other words, farmers may think that harvesting rainwater is appropriate behavior to engage in but they may not be as decided to do it. This hesitation may stem from a few reasons. One possible reason could be that farmers do not consider rainwater as a scarce resource as the Musanze district experiences rain throughout the year. Hence, there may not be any urgency for them to collect rainwater, leading them to be less decided to do it. In contrast to rainwater harvesting, the positive effect of attitude towards the use of fertilizer suggests that the more respondents perceive the use of organic fertilizer as a good, useful, and right practice, the more decided they are about their intention to use organic fertilizer to increase their harvest. From these findings, it can be concluded that increasing farmers' perception/knowledge about the benefits of using organic fertilizer is likely to lead farmers to use it in their agricultural activities.

In contrast to the rainwater and fertilizer models, attitude towards alternative sources of energy did not prove to have any significant influence on behavioral intent. This finding diverges from what the Theory of Planned Behavior (TPB) suggests. Despite this discrepancy, the literature suggests that not all previous studies found a significant relationship between attitude and behavioral intent. For example, while applying the TPB to study the motivations to participate in riparian improvement programs, Corbett (2002) found no significant effect on attitude on the prediction of behavioral intent. Some research even goes as far as to suggest that attitude does not always translate to behavioral intent or actual behavior. For instance, Heberlein (2012) argued that despite the popular belief "*positive attitudes toward a resource are not necessarily linked to positive conservation action",* and concluded that while attitudes are important, they are not everything.

Norms: As results showed, descriptive and injunctive norms had a significant influence on behavioral intent across all models. This means that what people who are important to you are doing and what they think you should do have an influence on your behavioral intent. This finding supports what the TPB suggests. Moreover, these findings support several studies that found an influence of descriptive and injunctive norms on behavioral intent. For instance, Niemiec et al. (2020)'s analysis of multiple studies on the impact of norms on environmental behavior observed that descriptive norms had a significant influence on behavior in the majority of the studies analyzed. Similarly, Smith et al. (2012) demonstrated that both descriptive and injunctive norms have an influence on pro-environmental behavior. In the case of rainwater and organic fertilizer, these findings suggest that actions and recommendations from family, friends, and neighbors influence farmers' decisions to harvest rainwater or use organic fertilizer.

The negative effect of descriptive and injunctive norms on the energy model suggests that what people (those who are important to farmers) are doing and what they think one should do may lessen the degree to which one is decided about engaging in the behavior. As was revealed by the results of this study, most farmers reported that they do not intend to use alternative sources of energy. The reluctance to engage in the use of alternative sources of energy may be explained by the potential cost involved as most farmers reported that it would be expensive to use these sources of energy. Given these two results, it would be expected that when people (especially, those who are important to you) say that they will not engage in something, you would be less decided to do it even if you felt that it is the right thing to do. Hence, the negative influence of descriptive and injunctive norms on the use of alternative sources of energy for domestic cooking. While promoting environmental behaviors that may incur a cost or a barrier at first (such as alternative sources of energy for domestic cooking), it is crucial to consider or at least be aware of how the target group's decision can be influenced by the actions and recommendations of farmers' family, friends, and neighbors.

The effect of subjective norms was only detected in the rainwater harvesting model, though very minimally. This finding suggested that the degree to which people who are important to you approve of what you do (rainwater harvesting in this case) can have an influence on your intention to engage in that behavior. This is supported by what TPB suggests and what some other studies found. For example, Gholamrezai et al. (2021) also found that the views of others (especially those who matter to you) are influential on your environmental behaviors. This finding indicates how the opinions and approval of family, friends, and neighbors have an influence on farmers' decisions to engage in environmental behavior such as rainwater harvesting. In contrast to rainwater harvesting, the influence of subjective norms on behavioral intent both in fertilizer and energy models was not significant. Although this contrasts with what the TPB suggests, it is not uncommon in literature. For example, while modeling farmers' responsible environmental behaviors in Iran, Farani et al. (2019) found that subjective norms had no significant effect on farmers' environmental behavior. Similarly, Botetzagias et al. (2015) found that subjective norms exerted no significant influence on behavioral intention to engage in environmental behavior such as recycling. However, Thøgersen (2014) argues that caution should always be exercised while dealing with subjective norms as most studies may underestimate the effect of subjective norms on behavioral intent.

Perceived behavior control: As shown by the results, perceived behavioral control only had a significant effect on behavioral intent in the energy model. In addition to aligning with the TPB, which considers perceived behavior control to be an important factor in determining behavioral intent, other studies found similar results. For example, Dijk et al. (2016) examined the factors that underlie farmers' intention to perform unsubsidized agri-environmental measures and found perceived behavior control to be among the main factors. Likewise, Yazdanpanah et al. (2014) found that perceived behavior control was one of the factors that significantly influenced behavioral intent. These findings are further supported by several other studies, including Defrancesco et al. (2008); Läpple & Kelley (2013); Botetzagias et al. (2015); and Kuhfuss et al. (2016). The negative sign on the energy model unsurprisingly suggests that the more one believes that the use of alternative sources of energy is difficult to engage in, the less decided one is to engage in it. Consequently, interventions and programs that promote farmers' environmental behaviors should consider farmers' perception of the difficulty or ease of engaging in the behavior as this may determine whether farmers will engage in the behavior or not.

Unlike the case of the energy model, perceived behavior control proved non-significant in other models. The lack of effect of perceived behavior control on behavioral intent or behavior is surprising but not unusual. For instance, Dijk et al. (2016) found no association between farmers' perceived behavior control and their intention to perform environmental measures. Likewise, while exploring the determinants of willingness to purchase organic food, Voon et al. (2011) found that perceived behavioral control had no significant effect on willingness to purchase organic food. Shaw and Chenoweth (2011) found similar results while exploring determinants of stormwater management. Lastly, it is worth noting that although stronger intention implies higher likelihood to engage in a given behavior (Azjen, 1991), translating the intention into an actual behavior is not always guaranteed. This may happen because of some behaviors are simply out of one's volitional control (Barlett, 2019). For example, even if a farmer has strong intentions to use alternative sources of energy (e.g., improved cooking stove), he or she may not have the financial resources to afford the required tools and services.

Background factors: the three models proved that the background factors' role in determining the behavioral intent through their influence on the three main factors of behavioral intent. This finding confirmed the premise of this study to use the Reasoned Action Approach, an extension of the TBP to include background factors in addition to TPB factors. Background factors in this study were mainly sociodemographic variables. Results showed that these variables had differing effects based on the factor and behavior considered. For example, the significant relationship between age and behavioral intent on energy use suggests that the older one is, the more likely they intend to use alternative sources of energy for domestic cooking. This finding accords with other findings such as Poortinga et al. (2004) who found a significant association between age and environmental behavior. Likewise, Diekmann and Preisendorfer (1999), Chen et al. (2011), and Bronfman et al. (2015), and found a similar relationship. This finding suggests that interventions that target older farmers in encouraging the use of alternative sources of energy for domestic cooking are more likely to yield successful results.

In addition to age, income proved to exert a significant effect on environmental behaviors. This finding implies that the higher the farmers' monthly income, the higher the degree to which they are decided to engage in environmental behavior. This is not surprising as adopting some environmental practices (such as energy-saving cooking) typically involves cost. The association between income and the intention to engage in environmental behavior has also been found by other studies. For example, Poortinga et al. (2004) found a positive relationship between income and energy use. Similarly, Gadenne et al. (2011) found that people with low income are less likely to engage in environmental behaviors than their peers. To encourage environmental behaviors among farmers, then, it may be effective to help them improve their economic status. This may include engaging them in programs or activities that are likely to increase their income.

Land ownership was also found to have a significant relationship with behavioral intent. In the case of fertilizer use, the positive effect indicates that owning land increases the degree to which farmers are decided to use organic fertilizer. This finding lends support to the notion that when farmers have land, they are more likely to use organic fertilizer. Mao et al. (2021) found a similar relationship while analyzing the effect of land ownership and the use of fertilizer among farmers. This finding suggests that improving farmers' opportunities to own land will increase the likelihood for farmers to engage in environmental behaviors, especially if they are related to land.

Limitations of the study

Some limitations of this study should be mentioned. First, the study was cross-sectional; thus, it discusses environmental behaviors and intentions as captured during the specified time. Moreover, data were collected during the Corona virus (COVID-19) pandemic, and no assumption is made that the same behaviors and intentions would be the same if data were gathered at a different time. Second, data should be construed as representative of the population of the northern part of Rwanda – specifically, the Musanze district – since the sample was restricted within the boundaries of the Musanze district; as such, it does not necessarily represent the behaviors and intentions of farmers across the whole country. Further analysis should be performed to account for geographical/climatological differences or other differences.

Another limitation to acknowledge concerns the use of SEM models. The goodness-of-fit indices for SEM only reflect results from models as specified in the measurement stage of the SEM modeling. It is likely that specifying the model differently would have yielded different goodness-of-fit indices. For example, a comparison of models that had no background factors with models that had background factors showed slightly different results of goodness-of-fit, with the former having better fit than the latter (see table 2.23 in appendix 2.1). Additionally, these models depend upon factors (latent variables) as constructed from factor analysis conducted during the exploratory factor analysis. Making some changes to factor analysis or using a different dimensionality reduction method (such as Principal Component Analysis) may result in different factors or number of factors. As such, the models presented in this study should be construed as applicable to this study and as specified in the measurement stage, not as a general model.

Conclusions

This study investigated the influence of attitudes, subjective norms, and perceived behavior control on farmers' behavioral intent to engage in environmental behavior behaviors. Overall, the study's results substantiated the notion that attitudes, subjective norms, and perceived behavioral control exert an influence on farmers' behavioral intent. As results revealed, the influence of factors and the direction of the influence can vary depending on the behavior considered. Additionally, the study showed that background factors play an important role in determining farmers' intention to engage in environmental behaviors, thus confirming the TPB's extension, the RAA approach, can explain people's behavior by including background factors in addition to attitude, subjective norms, and perceived behavior control.

Overall, the study provides insights that may guide programs and interventions that seek to promote environmental behaviors among farmers. For example, in the context of the current study, it was clear that farmers are more likely to engage in environmental behaviors if they perceive the behavior to be a good, useful, and right practice. Thus, agricultural programs should focus on promoting environmental behaviors (such as the use of alternative source of energy) as the good, useful, and right practices to adopt if farmers want to protect the environment.

Moreover, farmers are likely to be decided to engage if their family, friends, and neighbors do the same, recommend the same, or approve of that behavior. The implication of this finding is that agricultural programs can leverage the importance that farmers place in the opinions and suggestions of their neighbors and friends. This could be leveraged by encouraging farmers to adopt environmental practices by reminding them that their part in the protection of the environmental could help spur others (neighbors, friends, or family members) to play their part as well.

Farmers will engage in a given behavior if they know that the behavior is not difficult to undertake. Thus, program designers can target farmers whose perception of their ability is high as these are the ones who are more likely to adopt these practices. However, program designers and policy-makers must be mindful of farmers' volitional ability. That is, programs that promote environmental behaviors and practices among farmers must also investigate whether farmers have the ability to translate their intentions into actual practices. This is crucial because it does not matter whether farmers are willing to adopt environmental practices if they are not capable of actually implementing them due to constraints beyond their ability (e.g., financial costs).

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Appendix

Appendix 2.1: Tables

Table 2-8: Summary statistics for education among farmers in Musanze district, 2019

	Primary		**Post-primary**		**Secondary**		**University**	
Years completed	Frequency	%	Frequency	%	Frequency	%	Frequency	%
0	27	6.98	133	71.51	122	34.66	173	90.58
1	22	5.68	32	17.20	34	9.66	3	1.57
2	52	13.44	16	8.60	57	16.19	3	1.57
3	71	18.35	4	2.15	42	11.93	5	2.62
4	84	21.71	-	0.00	26	7.39	7	3.66
5	55	14.21	1	0.54	15	4.26	-	-
6	67	17.31	-	-	56	-	-	-
7	9	2.33	-	-	-	-	-	-

Table 2-9: Summary responses (%) on farmers' attitudes towards different behaviors relative to natural resources in Musanze District, Rwanda, 2021

	Rainwater *(%)*	**Alternative energy** *(%)*	**Charcoal** *(%)*	**Fuelwood** *(%)*	**Organic fertilizer** *(%)*	**Inorganic fertilizer** *(%)*
	For me, harvesting rainwater is	*For me, using alternative sources of energy for cooking is*	*For me, using charcoal is*	*For me, using fuelwood is*	*For me, using organic fertilizer is*	*For me, using inorganic fertilizer is*
2: Bad	11.73	2.03	5.38	10.70	0.68	13.48
3: Neither bad nor good	5.44	9.98	3.53	6.62	3.55	3.58
4: Good	65.82	77.33	77.48	47.37	50.51	62.12
5: Very good	17.01	10.66	13.61	35.31	45.27	20.82
	n= 588	*n=591*	*n=595*	*n=589*	*n=592*	*n=586*
1: Very wrong	1.62	0.19	0.18	1.43	0.00	0.42
4: Right	78.70	87.69	84.66	56.15	53.19	74.06
5: Very right	19.68	12.12	15.16	42.42	46.81	25.52
	n=493	*n=528*	*n=541*	*n=488*	*n=564*	*n=478*
1: Very useless	2.91	0.00	0.00	0.69	0.00	0.57
2: Useless	21.51	4.32	3.64	7.24	1.02	13.71
3: Neither useless nor useful	14.53	40.29	14.55	13.79	6.83	9.71
5: Very useful	61.05	55.40	81.82	78.28	92.15	76.00
	n=172	*n=139*	*n=110*	*n=290*	*n=293*	*n=175*
1: Very inexpensive	–	9.09	3.25	12.08	0.50	44.11
2: Inexpensive	–	26.36	33.43	36.83	31.34	16.54
3: Neither inexpensive nor expensive	–	10.00	13.31	16.63	12.19	7.02
5: Very expensive	–	54.55	50.00	34.46	55.97	32.33
		n=440	*n=338*	*n=505*	*n=402*	*n=399*

Table 2-10: Summary responses (%) on farmers' social norms (subjective norms, descriptive norms, and injunctive norms) relative to different natural resources in Musanze District, Rwanda, 2021

A. Subjective norms

(What the following groups of people approve or disapprove of doing about different environmental behaviors)

Question: To what extent do these groups approve or disapprove of each of the following activities?
Response categories: 1: Disapprove very much; 2:Disapprove; 3: Neither disapprove nor approve; 4: Approve; and 5: Approve very much

	Neighbors			***Family members***			***Friends***		
	Harvest rainwater	Use organic fertilizer	Use alternative sources of energy	Harvest rainwater	Use organic fertilizer	Use alternative sources of energy	Harvest rainwater	Use organic fertilizer	Use alternative sources of energy
	%	%	%	%	%	%	%	%	%
4	34.01	35.29	66.57	32.36	35.39	64.07	31.99	34.38	62.94
5	65.99	64.71	33.43	67.64	64.61	35.93	68.01	65.62	37.06
	n=544	*n=578*	*n=332*	*n=547*	*n=568*	*n=334*	*n=547*	*n=573*	*n=340*

B. Descriptive norms

(What the following groups of people do about different environmental behaviors)

To what extent do you agree or disagree with the following statements?
(Response categories: 1: Completely disagree; 2:Disagree; 3: Neither disagree nor agree; 4: Agree; and 5: Completely agree)

	My neighbors			***My family members***			***My friends***		
	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer
	%	%	%	%	%	%	%	%	%
1	0.67	18.61	0.34	0.68	17.89	0.17	0.68	17.72	0.34
2	5.72	30.96	1.01	4.58	34.07	0.51	5.44	33.39	0.85
3	4.38	13.71	2.52	3.90	14.14	2.54	3.57	15.16	1.69
4	67.17	35.70	49.75	67.23	33.39	49.49	66.84	32.54	50.68
5	22.05	1.02	46.39	23.60	0.51	47.29	23.47	1.19	46.44
	n=594	*n=591*	*n=595*	*n=589*	*n=587*	*n=590*	*n=588*	*n=587*	*n=590*

C. Injunctive norms

(What the following groups of people think I should do about different environmental behaviors)

To what extent do you agree or disagree with the following statements?
(Response categories: 1: Completely disagree; 2: Disagree; 3: Neither disagree nor agree; 4: Agree; and 5: Completely agree)

	My neighbors think I should			***My family members think I should***			***My friends think I should***		
	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer	Harvest rainwater	Use alternative sources of energy	Use organic fertilizer
	%	%	%	%	%	%	%	%	%
1	0.34	18.04	0.85	0.51	17.47	0.51	0.34	18.46	0.85
2	5.60	24.05	1.88	5.30	24.14	2.40	5.95	21.54	1.36
3	2.72	19.93	2.73	2.91	19.69	1.72	2.38	21.03	2.37
4	70.63	37.11	50.34	71.62	37.50	52.32	70.41	38.29	52.71
5	20.71	0.86	44.20	19.66	1.20	43.05	20.92	0.68	42.71
	n= 589	*n=582*	*n=586*	*n=585*	*n=584*	*n=583*	*n=588*	*n=585*	*n=590*

Table 2-11: Summary responses (%) of the extent to which different groups (neighbors, family members, and friends) are to respondents in Musanze district, Rwanda, 2021

How important are these groups of people to you?			
	Neighbors *(%)*	***Family*** *(%)*	***Friends*** *(%)*
1: Very unimportant	0.00	0.00	0.18
2: Unimportant	1.81	3.19	0.36
4: Important	54.33	43.26	59.49
5: Very important	43.86	53.55	39.96
	n=554	*n=564*	*n=548*

Table 2-12: Summary responses (%) of respondents' intention (and the degree of intention) to engage in different environmental behaviors in Musanze district, Rwanda, 2021

	Intention rainwater *(%)*	**Intention pellets** *(%)*	**Intention improved cooking stoves** *(%)*	**Intention LPG gas** *(%)*	**Intention organic fertilizer** *(%)*
	During the next rainy season, do you intend to harvest rainwater to increase water quantity in your household?	During the next month, do you intend to use pellets as the main source of fuel for cooking?	During the next month, do you intend to use improved cooking stoves as the main source of fuel for cooking?	During the next month, do you intend to use LPG (gas) as the main source of fuel for cooking?	During the next month, do you intend to use organic fertilizer to increase your harvest?
0: No	8.72	96.31	55.87	89.24	4.21
1: Yes	91.28	3.69	44.13	10.76	95.79
	n=596	*n*=597	*n*=596	*n*=595	*n*=594

	Intention degree rainwater *(%)*	**Intention degree pellets** *(%)*	**Intention degree improved cooking stoves** *(%)*	**Intention degree LPG gas** *(%)*	**Intention degree organic fertilizer** *(%)*
	To what degree are you decided or undecided to harvest rainwater to increase water quantity in your household in the next rainy season?	To what degree are you decided to use pellets as the main source of fuel for cooking next month?	To what degree are you decided to use improved cooking stoves as the main source of fuel for cooking next month?	To what degree are you decided to use LPG (gas) as the main source of fuel for cooking next month?	To what degree are you decided or undecided to use organic fertilizer to increase your harvest next month?
	Response categories: 1: Very undecided; 2: Undecided; 3: Neither undecided nor decided; 4: Decided; 5: Very decided				
1	0.17	6.89	1.51	27.95	0.17
2	2.35	41.18	23.32	26.94	1.18
3	3.19	0.67	3.52	4.38	3.36
4	66.72	30.59	55.54	22.56	61.34
5	27.56	20.67	16.11	18.18	33.95
	n=595	*n*=595	*n*=596	*n*=594	*n*=595

Table 2-13: Loadings matrix after an orthogonal rotation to identify the factors for the "attitude" items subscale. Data collected from farmers (n=604) in Musanze district, Rwanda, 2021

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 7**
	Attitude towards expensiveness	Attitude towards rainwater	Attitude towards fuelwood	Attitude towards inorganic fertilizer	Attitude towards organic fertilizer	Attitude towards alternative sources of energy	Attitude towards charcoal
D1	0	**0.91**	0.09	-0.01	0.09	-0.04	0.11
D2	0	**0.87**	0.05	0.1	0.01	-0.02	0.11
D3	-0.03	**0.62**	0.12	0	0.03	-0.02	0.03
D4	0	0.01	-0.06	0	0.14	**0.98**	0.08
D5	-0.06	-0.06	-0.12	0.09	0.08	**0.65**	0.12
D6	-0.03	0	-0.03	0.07	-0.04	**0.49**	-0.01
D7	**-0.9**	-0.03	-0.07	0.04	-0.08	0.08	-0.03
D8	0.06	0.17	0.16	0.06	0.01	0.04	**0.96**
D9	0.02	-0.01	-0.02	0.12	0.04	0.07	**0.66**
D10	0.09	0.19	-0.11	0.13	0.01	0.08	**0.33**
D11	**-0.57**	0.08	-0.04	0.16	0.07	0.06	0.11
D12	0.25	0.08	**0.93**	0.01	0.08	-0.06	0.06
D13	0.21	0.07	**0.79**	0.1	0.06	-0.1	0.04
D14	0.01	0.13	**0.66**	-0.17	0.09	-0.1	-0.07
D15	**0.75**	0.08	0.14	0.09	0.21	-0.02	0.14
D16	0.27	0.05	0.08	0.08	**0.95**	0.02	0.07
D17	0.4	0.03	0.06	0.15	**0.77**	0.03	0.1
D18	-0.1	0.06	0.08	-0.09	**0.58**	0.08	-0.04
D19	**0.44**	0.19	0.25	0.31	0.19	0.05	0.12
D20	-0.09	0.09	0.07	**0.88**	0	0.07	0.22
D21	-0.08	0.05	-0.05	**0.79**	-0.04	0.04	0.04
D22	0.28	-0.06	-0.09	**0.65**	0.11	0.14	0.11
D23	**-0.74**	0.1	-0.17	-0.12	-0.12	-0.01	-0.13

Table 2-14: Loadings matrix after an orthogonal rotation to identify the factors for the "subjective norms" items subscale. Data collected from farmers (n=604) in Musanze district, Rwanda, 2021

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**
	Descriptive and injunctive norms – Alternative sources of energy	Descriptive and injunctive norms – Rainwater	Descriptive and injunctive norms – Organic fertilizer	Subjective norms – Alternative sources of energy	Subjective norms – Organic fertilizer	Subjective norms – Rainwater
E1_Rain	0.03	0.23	0.04	0.17	0.34	**0.61**
E2_Rain	0.08	0.19	0.09	0.22	0.33	**0.64**
E3_Rain	0.06	0.18	0.07	0.13	0.25	**0.9**
E1_Fer	-0.02	-0.03	0.11	0.13	**0.73**	0.21
E2_Fer	0.03	-0.04	0.17	0.13	**0.87**	0.17
E3_Fer	0.05	-0.02	0.18	0.13	**0.75**	0.29
E1_En	0.07	0.07	0.06	**0.78**	0.13	0.12
E2_En	0.14	-0.06	0.07	**0.89**	0.16	0.07
E3_En	0.18	-0.1	0.06	**0.81**	0.1	0.19
E5B	-0.06	**0.89**	0.09	-0.03	0.01	0.07
E8	-0.09	**0.85**	0.11	-0.06	0	0.09
E11	-0.03	**0.91**	0.06	-0.02	0.01	0.09
E14	-0.08	**0.87**	0.12	0.03	0	0.07
E17	-0.02	**0.88**	0.12	-0.02	-0.03	0.1
E20	-0.04	**0.92**	0.11	0.01	-0.02	0.11
E6B	**0.84**	-0.08	0.2	0.07	0.04	0.03
E9	**0.85**	-0.06	0.21	0.12	0.02	0.08
E12	**0.87**	-0.08	0.2	0.13	0.01	0.05
E15	**0.92**	-0.03	0.14	0.06	0.03	0.01
E18	**0.92**	-0.05	0.12	0.07	-0.01	0.03
E21	**0.93**	-0.05	0.13	0.05	0.01	-0.01
E7_Fer	0.12	0.08	**0.66**	0.06	0.1	0.06
E10_Fer	0.12	0.17	**0.7**	0	0.12	0.04
E13_Fer	0.11	0.16	**0.71**	0.04	0.12	0.07
E16_Fer	0.16	0.03	**0.88**	0.07	0.08	0.01
E19_Fer	0.24	0.09	**0.87**	0.04	0.07	0.01
E22_Fer	0.18	0.04	**0.92**	0.04	0.04	0.02

Table 2-15: Results for the reliability test (Cronbach alpha) for latent item subscales in the data collected from farmers (n=604) in Musanze district, 2021

Subscale	**Value** (Cronbach's alpha)	**Meaning***
Environmental behavior	0.43	Low reliability
Attitude	0.77	High reliability
Norms (all)	0.89	High reliability
Behavioral intent	0.78	High reliability

**According to Hinton et al. (2004)'s guide*

Table 2-16: Comparison of SEM models

Fit indices without background factors			
Model	*rmsea*	*cfi*	*srmr*
Rainwater	0.079	0.958	0.043
Fertilizer	0.066	0.969	0.071
Energy	0.091	0.945	0.075

Fit indices with background factors			
Model	*rmsea*	*cfi*	*srmr*
Rainwater	0.085	0.913	0.137
Fertilizer	0.068	0.934	0.112
Energy	0.088	0.907	0.107

Appendix 2.2: Figures

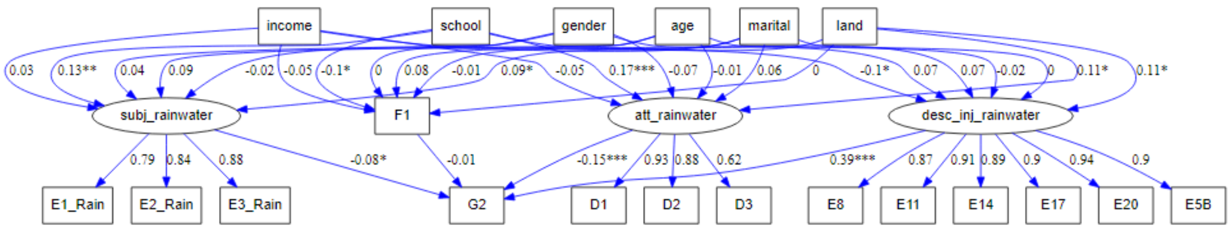

Figure 2-7: Model path for the rainwater model

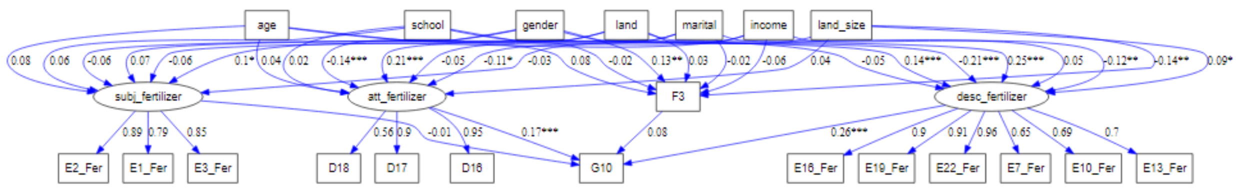

Figure 2-8: Model path for the fertilizer model

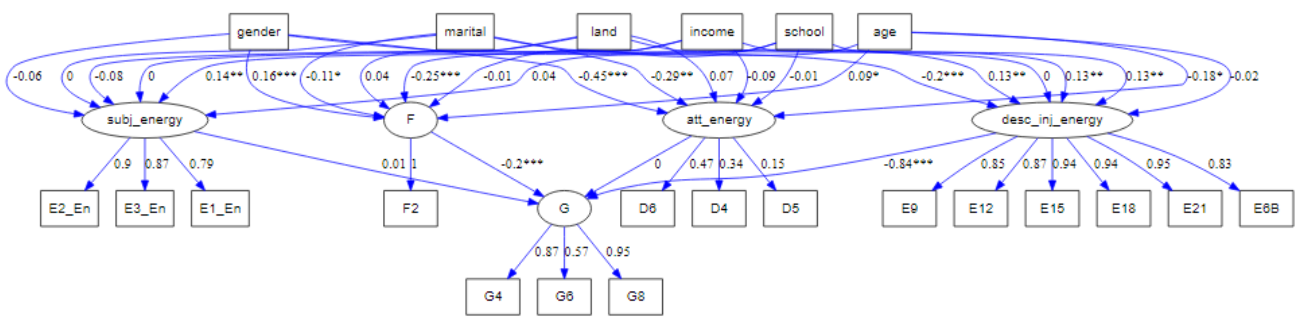

Figure 2-9: Model path for the energy model

Appendix 2.3: Questionnaire

Hi, my name is ____ and would like to ask you a few questions about a survey designed by the University of Tennessee Institute of Agriculture. I'd like to speak to the head of the household or the person who makes decisions in the households. The questions are about behaviors and attitudes towards natural resources and the environment.

[**Note to enumerator**: For the correct person, please read the information on the informed consent form]

Who is responding?

1. Survey test respondent
2. Pilot survey respondent
3. Survey respondent

A. Screening questions

A.1. Are you the person responsible for making decisions for your HH?

1. Yes
2. No

[Note to enumerator]: If no, ask if you can speak to the right person or record the time when would be the best to come back to speak to the right person.

A.2. Role of respondent in the household

1. Head of household
2. Spouse of the head of household
3. Child
4. Other [Specify: ______________________________]

[**Note to enumerator**]: If the response is "Child", stop the survey or ask if you can find an adult in the household who can respond. We can only survey people greater than or equal to 18 years old

A.3. Do you or does anyone in your household work in the agriculture sector?

1. Yes
2. No

A.4. Do you or does anyone in your family do one or more of the following activities?

	Yes	No
Cultivate(s) land		
Grow(s) crops		
Raise(s) animals/livestock		
Work(s) as extension worker		
Sell(s) different crops and produce in the market		
Sell(s) livestock or livestock products in the market		

B. Natural resources management

B.1. Do you have running water supply in your household?

1. Yes
2. No

[Skip logic] If yes, go to question B.3.; otherwise proceed with question B.2.

B.2 Approximately, by walking, how far is the closest main/primary source of water from your household?

1. Within 10 minutes
2. Between 11 minutes and 30 minutes
3. Between 31 minutes and 60 minutes
4. More than 60 minutes

B.3. Which of the following activities of water conservation do you use in your household?

1. Harvest rainwater from roofs
2. Reduce the amount of water to use for different activities
3. Reuse water from one activity for other activities
4. None of the above

B.4. How frequently does your household use the following sources of energy for cooking as primary source of energy?

	Never	Rarely	Sometimes	Frequently	Very frequently
Charcoal					
Fuelwood/firewood					
Pellets					
LPG (Gas)					
Electricity					
Biogas					

[Skip logic] If charcoal or fuelwood are used, continue; otherwise, go to question B.6.

B.5. What cooking stoves or cooking setup does your household use?
1. Traditional cooking setup (three rocks)
2. Regular cooking stove
3. Improved cooking stove
4. Other [Specify: ____________________]

B.6. Does your household use fertilizers to increase agricultural production?
1. Yes
2. No

B.7. What kind of fertilizers does your household use?
1. Organic
2. Inorganic
3. Both

C. Environmental behaviors

C.1. During the recent rainy month, how many times per week have you collected rainwater?
1. None
2. One to two days a week
3. Three to four days a week
4. Five to six days a week
5. Seven days a week

C.2. During last month, how many days have you used improved cooking stoves for cooking?
1. None
2. One to two days a week
3. Three to four days a week
4. Five to six days a week
5. Seven days a week

C.3. During last month, how many days have you used Pellets for cooking?

6. None
7. One to two days a week
8. Three to four days a week
9. Five to six days a week
10. Seven days a week

C.4. During last month, how many days have you used biogas for cooking?

1. None
2. One to two days a week
3. Three to four days a week
4. Five to six days a week
5. Seven days a week

C.5. During last month, how many days have you used LPG (gas) for cooking?

1. None
2. One to two days a week
3. Three to four days a week
4. Five to six days a week
5. Seven days a week

C.6. How frequently or rarely have you used organic fertilizer to increase your agricultural production?

1. Never
2. Rarely
3. Sometimes
4. Frequently
5. Very frequently

D. Attitudes

D.1. For me, harvesting rainwater is

1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.2. For me, harvesting rainwater is

1. Very wrong
2. Wrong
3. Neither wrong nor right
4. Right
5. Very right

D.3. For me, harvesting rainwater is

1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

Alternative sources (other than charcoal or fuelwood)
Using alternative sources of energy include using improved cooking stoves, Pellets, Biogas, or LPG (gas)
D.4. For me, using alternative sources of energy for cooking is
1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.5. For me, using alternative sources of energy for cooking is
1. Very wrong
2. Wrong
3. Neither wrong nor right
4. Right
5. Very right

D.6. For me, using alternative sources of energy for cooking is
1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

D.7. For me, using alternative sources of energy for cooking is
1. Very inexpensive
2. Inexpensive
3. Neither inexpensive nor expensive
4. Expensive
5. Very expensive

Charcoal
D.8. For me, using charcoal is
1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.9. For me, using charcoal is
1. Very wrong
2. Wrong
3. Neither wrong nor right
4. Right
5. Very right

D.10. For me, using charcoal is
1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

D.11. For me, using charcoal is
1. Very inexpensive
2. Inexpensive
3. Neither inexpensive nor expensive
4. Expensive
5. Very expensive

Fuelwood

D.12. For me, using fuelwood is
1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.13. For me, using fuelwood is
1. Very wrong
2. Wrong
3. Neither wrong nor right
4. Right
5. Very right

D.14. For me, using fuelwood is
1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

D.15. For me, using fuelwood is
1. Very inexpensive

2. Inexpensive
3. Neither inexpensive nor expensive
4. Expensive
5. Very expensive

Organic fertilizer

D.16. For me, using organic fertilizer is

1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.17. For me, using organic fertilizer is

1. Very wrong
2. Wrong
3. Neither wrong nor right
4. Right
5. Very right

D.18. For me, using organic fertilizer is

1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

D.19. For me, using organic fertilizer is

1. Very inexpensive
2. Inexpensive
3. Neither inexpensive nor expensive
4. Expensive
5. Very expensive

Inorganic fertilizer

D.20. For me, using inorganic fertilizer is

1. Very bad
2. Bad
3. Neither bad nor good
4. Good
5. Very good

D.21. For me, using inorganic fertilizer is

1. Very wrong
2. Wrong

3. Neither wrong nor right
4. Right
5. Very right

D.22. For me, using inorganic fertilizer is
1. Very useless
2. Useless
3. Neither useless nor useful
4. Useful
5. Very useful

D.23. For me, using inorganic fertilizer is
1. Very inexpensive
2. Inexpensive
3. Neither inexpensive nor expensive
4. Expensive
5. Very expensive

E. Subjective norms

[Read to the respondent] Environmental behaviors include actions such as harvesting rainwater, using organic fertilizer, or using alternative energy for cooking.

E.1.

To what extent do your **neighbors** approve or disapprove of each of the following activities?					
	Disapprove very much	*Disapprove*	*Neither disapprove nor approve*	*Approve*	*Approve very much*
Harvesting rainwater					
Using organic fertilizer					
Using alternative energy for cooking					

E.2.

To what extent do your **family members** approve or disapprove of each of the following activities?					
	Disapprove very much	*Disapprove*	*Neither disapprove nor approve*	*Approve*	*Approve very much*
Harvesting rainwater					
Using organic fertilizer					
Using alternative energy for cooking					

E.3.

To what extent do your **friends** approve or disapprove of each of the following activities?					
	Disapprove very much	*Disapprove*	*Neither disapprove nor approve*	*Approve*	*Approve very much*
Harvesting rainwater					
Using organic fertilizer					
Using alternative energy for cooking					

E.4. How important are your neighbors to you?
1. Very unimportant
2. Unimportant
3. Neither unimportant nor important
4. Important
5. Very important

E.5. How important are your family members to you?
1. Very unimportant
2. Unimportant
3. Neither unimportant nor important
4. Important
5. Very important

E.6. How important are your friends to you?
1. Very unimportant
2. Unimportant

3. Neither unimportant nor important
4. Important
5. Very important

Descriptive subjective norms

E.5. Most of my neighbors harvest rainwater to increase the quantity of water in their household
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.6. Most of my neighbors use alternative sources of energy for cooking
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.7. Most of my neighbors use organic fertilizer to increase their agricultural production?
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.8. Most of my family members harvest rainwater to increase the quantity of water in their household
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.9. Most of my family members use alternative sources of energy for cooking
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.10. Most of my family members use organic fertilizer to increase their harvest?
1. Completely disagree
2. Disagree

3. Neither disagree nor agree
4. Agree
5. Completely agree

E.11. Most of my <u>friends</u> harvest rainwater to increase the quantity of water in their household

1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.12. Most of my friends use alternative sources of energy for cooking

1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.13. Most of my friends use organic fertilizer to increase their harvest

1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

Injunctive local norms

E.14. Most of my neighbors think that I should harvest rainwater

1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.15. Most of my neighbors think that I should use alternative sources of energy for cooking

1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.16. Most of my neighbors think I should use organic fertilizer to increase my agricultural production?

1. Completely disagree
2. Disagree
3. Neither disagree nor agree

4. Agree
5. Completely agree

E.17. Most of my family members think that I should harvest rainwater
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.18. Most of my family members think that I should use alternative sources of energy for cooking
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.19. Most of my family members think I should use organic fertilizer to increase my agricultural production?
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.20. Most of my friends think that I should harvest rainwater
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.21. Most of my friends think that I should use alternative sources of energy for cooking
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree
5. Completely agree

E.22. Most of my friends think I should use organic fertilizer to increase my agricultural production?
1. Completely disagree
2. Disagree
3. Neither disagree nor agree
4. Agree

5. Completely agree

F. Perceived behavioral control

F.1. For me, harvesting rainwater to increase water quantity in the household would be

1. Very easy
2. Easy
3. Neither easy nor difficult
4. Difficult
5. Very difficult

F.2. For me, using alternative sources of energy for cooking would be

1. Very easy
2. Easy
3. Neither easy nor difficult
4. Difficult
5. Very difficult

F.3. For me, using organic fertilizer to increase harvest would be

1. Very easy
2. Easy
3. Neither easy nor difficult
4. Difficult
5. Very difficult

G. Intention

G.1. During the next rainy season, do you intend to harvest rainwater to increase water quantity in your household?

1. Yes
2. No

G.2. To what degree are you decided or undecided to harvest rainwater to increase water quantity in your household in the next rainy season?

1. Very undecided
2. Undecided
3. Neither undecided nor decided
4. Decided
5. Very decided

G.3. During the next month, do you intend to use pellets as the main source of fuel for cooking?

1. Yes
2. No

G.4. To what degree are you decided to use pellets as the main source of fuel for cooking next month?

1. Very undecided
2. Undecided

3. Neither undecided nor decided
4. Decided
5. Very decided

G.5. During the next month, do you intend to use improved cooking stoves as the main source of fuel for cooking?

1. Yes
2. No

G.6. To what degree are you decided to use improved cooking stoves as the main source of fuel for cooking next month?

1. Very undecided
2. Undecided
3. Neither undecided nor decided
4. Decided
5. Very decided

G.7. During the next month, do you intend to use LPG (gas) as the main source of fuel for cooking?

1. Yes
2. No

G.8. To what degree are you decided to use LPG (gas) as the main source of fuel for cooking next month?

1. Very undecided
2. Undecided
3. Neither undecided nor decided
4. Decided
5. Very decided

G.9. During the next 3 months, do you intend to use organic fertilizer to increase your harvest?

1. Yes
2. No

G.10. To what degree are you decided or undecided to use organic fertilizer to increase your harvest in the next 3 months?

1. Very undecided
2. Undecided
3. Neither undecided nor decided
4. Decided
5. Very decided

H. Socioeconomics

H.1. Residence

Sector

Cell
Village

H.2. Coordinates
[**note to enumerator**: Ensure that the device's functionality for recording coordinates is turned on and record the coordinates from the device]

H.3. Gender
1. Male
2. Female

H.4. In what year were you born?

H.5. What is your marital status?
1. Never married
2. Married
3. Separated
4. Widowed
5. Divorced

H.6. Has anyone in the household ever attended school?
1. Yes
2. No

H.7. Number of years of school successfully completed by anyone in the house at that level
1. Pre-school 0 1 2 3
2. Primary 0 1 2 3 4 5 6
3. Post-primary 0 1 2 3
4. Secondary 0 1 2 3 4 5 6 7
5. University 0 1 2 3 4 5 6 7+

H.8. On the following scale, in what category of income does your highest monthly income in the household fall?
1. Below RWF 50,000
2. Between RWF 50,000 and RWF 100,000
3. Between RWF 100,000 and RWF 500,000
4. Above RWF 500,000

H.9. Do you or anyone in your household own land?
1. Yes
2. No

H.10. How big is the land that you or anyone in your household own?
1. Less than 1 ha

2. Between 1ha and 5 ha
3. More than 5 ha

CHAPTER III
SPATIAL ANALYSIS OF FARMERS’ ENVIRONMENTAL BEHAVIORS IN RWANDA

Abstract

One of the challenges facing the world is to increase food production while protecting the environment and natural resources. Meeting this challenge will require the adoption of agricultural practices that protect the environment. Given the role of agriculture in meeting this challenge, a better understanding of environmental behaviors among farmers provides an opportunity to promote the adoption of agricultural practices that align with the stewardship of the environment and natural resources. Various theories have been developed to explain people's behaviors. The most commonly applied theories include the Theory of Planned Behavior, the Socio-Cognitive Theory, or the Reasoned Action Approach. Several studies have applied these theories to investigate environmental behaviors among farmers and the factors that influence these behaviors. While these studies provide a good foundation for understanding farmers' behaviors, not many explicitly account for the spatial arrangement of observations. Specifically, no studies have attempted to study spatial aspects of behavioral intent to engage in different environmental behaviors. This study examined the spatial patterns of behavioral intent to harvest rainwater, use organic fertilizer, and use alternative sources of energy for domestic cooking. Data were randomly collected from 566 farmers in the Musanze district. Spatial analysis was conducted to assess global and local spatial autocorrelation. Results indicate the presence of global spatial autocorrelation on three variables. Further, local measures of spatial autocorrelation revealed the presence of clusters of significant spatial association. Results from this study provide a further understanding of farmers' environmental behaviors and behavioral intent in the Musanze district.

Keywords: Environmental Behavior; Behavioral intent; Spatial autocorrelation; Rwanda.

Introduction

Background of the study

Water scarcity is among the most pressing challenges in Rwanda. By 2010, daily per capita consumption of water was around 13 liters per day, a quantity lower than the standard consumption of 20 liters (MININFRA, 2013). In the northern part of Rwanda, where this study is conducted, the average water consumption per capita was estimated to be between 4.7 and 12.3 liters per day (Nkurunziza, 2016). Additionally, in this region, people collect water from more than 1 kilometer away from their households or take more than 30 minutes to collect water. Although Rwanda has taken laudable steps to improve water supply, projections continue to show a further increase in water demand (MININFRA, 2013; UNEP, 2010) resulting from population growth, urbanization, rapid economic development, and decreasing mortality rate (MINIRENA, 2012). Through intensification and industrialization, agriculture places further demands on water resources (NISR, 2019) and consumes more water than any other sector in Rwanda (over 65%) (Bizuhoraho et al., 2018). As water use increases, environmentally friendly behaviors such as water conservation offer a solution to water scarcity (Rockström et al., 2009). The main hurdle to the implementation of water conservation practices is that it often depends on public willingness to adopt these behaviors (Hurlimann et al., 2009). In the case of farmers, understanding whether they are willing to conserve water resources is crucial. This understanding is often achieved by assessing farmers' intention to conserve water as environmentally-oriented intention can often predict environmental action (Corbett, 2002; Yazdanpanah et al., 2014).

Fertilizer use constitutes another important behavior among farmers in Rwanda. Rwandan agriculture remains dominated by smallholder farming. Since agricultural productivity remains low, options like agricultural intensification offer an avenue to improve productivity, food security, and malnutrition. Agricultural intensification is even more relevant in a country like Rwanda where arable land is limited (IFDC, 2014). The Government of Rwanda (GoR) has developed the Strategic Plan for Agriculture Transformation (SPAT[10]) to raise annual agricultural growth to 6 percent or more and allocate at least 10 percent of the national budget to agriculture. Part of the SPAT is to increase fertilizer use, and the GoR has developed the fertilizer market and supports fertilizer utilization. This has resulted in a significant increase in nationwide fertilizer use, from 6,000 metric tons in 2006 to 34,000 metric tons in 2012. During these 6 years, the penetration rate (the number of farmers using fertilizers) has increased from 14 to 29% (MINAGRI, 2012). However, the returns of increased use of fertilizer and its agricultural productivity do not reflect environmental consequences (Uri, 1997). The adverse effects of fertilizers on the environment include algae blooms (which deplete oxygen in surface waters), pathogens and nitrates in drinking water, and the emission of odors and gases into the air (Berg et al., 2017). Other adverse effects include greenhouse gas emissions (methane and nitrous oxide), groundwater pollution with nitrates, and heavy-metal buildup in the soil (Lenka et al., 2016). In Rwanda, the use of fertilizer has been shown to have impacts on the environment

[10] See (MINAGRI, 2018) and (MINAGRI, 2012)

through the contamination of surface water resources or increasing greenhouse gas emissions, among others (World Green, 2016). According to Rwanda Environmental Management Authority (REMA, 2014), the impacts of fertilizer use in Rwanda were linked to the increasing use of inorganic fertilizer and decreasing use of organic fertilizer by farmers. It was found that once farmers start using inorganic fertilizer, they tend to stop using organic fertilizer. The recommended approach, thus, is to consider both approaches (inorganic and organic) to avert the potential adverse impacts of increased use of inorganic fertilizer on the environment. Since the use of organic fertilizer is considered to protect the environment, this study treats the use of organic fertilizer among farmers as an environmental behavior.

In addition to water use and fertilizer use, the use of alternative sources of energy for domestic cooking can be an important avenue to protect the environment. In Rwandan rural households, biomass consumption is still the primary source of energy for domestic cooking. As Slander and Hendriksen (2012) reported, as of 2011, approximately 86% of primary energy in Rwanda came from biomass, mainly in the form of wood; wood is either used directly as fuel (57%) or converted into charcoal (23%) together with smaller amounts of crop residues and peat (6%). Although the dependence on biomass has improved over the past two decades (from 95% to 86%), the ratio is still high (Bimenyimana et al., 2018). The heavy dependence on biomass has adverse effects on the environment in general (Bimenyimana et al., 2018; Mazimpaka, 2014). The inefficient use of solid fuels for cooking contributes to 3.8 million premature deaths every year (WHO, 2018). The adverse effects of biomass use on human health and the environment warrant a reduction in biomass consumption as a source of fuel for domestic cooking. One of the challenges facing Rwanda's energy sector is to produce and consume biomass-based energy without harming the environment (Munyaneza et al., 2016). Transitioning to more efficient alternative sources provides one of the options to reduce the dependence on biomass consumption. In Rwanda, for example, technologies that have the potential to reduce the consumption of charcoal include improved cookstoves, efficient charcoal production, efficient energy alternatives like biomass pellets, liquefied petroleum gas (LPG), and biogas (MININFRA, 2016). Farmers who use or are open to using these options are more likely to contribute to the protection of the environment. This study treats the use of alternative sources of energy for domestic cooking as an environmental behavior.

Environmental behavior

Environmental behaviors refer to individual behaviors that contribute to the sustainability of the environment and natural resources. These behaviors include engaging in activities such as limiting energy consumption, reducing waste or recycling (Mesmer-Magnus et al., 2013), engaging in waste management (Janmaimool & Denpaiboon, 2016), purchasing organic food (Voon et al., 2011), water conservation (Trumbo & Keefe, 2011), engaging in forest conservation efforts (Garekae et al., 2016) and others.

The theoretical foundation to explain behavior in this study is motivated by the Theory of Planned Behavior (TPB) as developed and improved by Ajzen & Fishbein (1977) and Azjen (1991). For years, the Theory of Planned Behavior (TPB) has been used to predict and explain behaviors. The TPB started as the Theory of Reasoned Action (TRA), which attempted to predict people's intention to engage in behavior by explaining the link between attitudes and behaviors within human action (Ajzen & Fishbein, 1977). The assumption was that people behave according to their attitudes and behavioral intentions. Moreover, the authors argued that people's decisions to engage in a given behavior depend on the expected outcome of their actions.

However, TRA did not include some factors that authors came to believe were important in explaining behaviors. For example, TRA did not include the notion of perceived control – it only focused on attitudes and norms. Consequently, the authors revised TRA and expanded it to address those limitations. The first iteration to improve the TRA became to develop the TPB, which included the notion of perceived control (Madden et al., 1992). As such, TPB became an improved theory developed to explain behaviors through the intention to engage in a given behavior (Azjen, 1991).

As the key factor in TPB, behavioral intent is the basis for an individual's motivation to perform a given action. Thus, the stronger the intention to engage in a given behavior, the more likely to engage in that behavior. Furthermore, the theory suggests that three predictors determine intention: attitudes, subjective norms, and perceived behavioral control. Attitudes in this context mean the evaluation (favorable or unfavorable) that individuals make towards the behavior to be performed. Subjective norms refer to perceived social pressure to engage in a given behavior. Perceived behavior control refers to people's perceptions of their ability to perform a given behavior (Azjen, 1991; Madden et al., 1992). According to the TPB, engaging in the behavior is done mainly through intentions. Intentions, in turn, are determined by attitudes, subjective norms, and perceived behavioral control (Azjen, 1991; Madden et al., 1992). Given that the crucial aspect of behavior is the intention or behavioral intent, this study focuses on behavioral intent. In particular, this study focuses on behavioral intent to engage in three environmental behaviors among farmers in Rwanda: rainwater harvesting, use of organic fertilizer, and use of alternative sources of energy for domestic cooking.

Environmental behavior, social interactions, and spatial patterns

People may behave in a certain way because of their spatial proximity to other people or the physical environment – this concept is sometimes referred to as local norms (Fornara et al., 2011). Passafaro et al. (2019) investigated local norms to understand the effects of spatial proximity on recycling intentions and self-reported behavior. Their findings indicate that spatial proximity directly influenced recycling behavior. They concluded that neighbors' influence to recycle waste is important in shaping the intention to behave. Additionally, residential proximity can also determine behavior; this means that residents of a given area may behave differently than non-residents of that area (Yoon et al., 2010). For example, Agovino et al. (2016) found that waste collection behavior tended to be strongly influenced by proximity; provinces with good levels of environmental pro-sociality were found to positively influence nearby ones. Similarly, Garekae et al. (2016) studied attitudes of local communities towards forest conservation in Botswana and found that community members in one village held stronger conservation attitudes towards a forest reserve than those living in the other two villages. Furthermore, Corral-Verdugo et al. (2002) studied residential water consumption and the motivation for conserving water. Their findings indicated that people were more motivated to reduce water consumption when their neighbors were also trying to reduce theirs. Li et al. (2013) found that people will be more likely to engage in fighting against pollution when the place of environmental pollution is closer to them.

The influence of proximity is derived from the idea that things that are close to each other are more similar than things that are farther apart, an idea that is expressed as the first law of geography (Tobler, 1979). This study argues that this law is relevant in explaining farmers' behavioral intent; i.e., behavioral intent may be more similar among farmers who live close to each other than among farmers who live apart from each other. The similarity of environmental behaviors may be driven by social interactions among farmers, especially those who live close to each other. For example, through social interactions, farmers may gain information about environmental protection from their neighbors or friends, and thus be influenced to do the same. Research shows that the link between environmental behavior and social interactions exists. For example, Zheng et al. (2019) empirically investigated the impact of social interaction on pro-environmental behavior in China. Their findings revealed that social interactions have a significant influence on environmental protection behavior. Furthermore, results showed that people may adjust their environmental protection behavior by directly observing what other people who are close to them are doing. This finding accords with various other studies whose results indicated a significant relationship between social interactions and environmental behaviors (Macias & Williams, 2014; Miller & Buys, 2008; Zhu, Wang, & Liu, 2021).

Further, research shows evidence that social interactions can underlie spatial patterns found in farmers' environmental behaviors. For instance, a study done by Tirkaso & Hailu (2022) concluded that spatial clusters at the sub-regional level reflected local farmers' interactions and the patterns of local resource use. Similarly, Boncinelli et al. (2016) not only found regional clustering in farmers' participation in environmental behaviors but also argued that the imitation among farmers could one reason to explain the diffusion of farmers' participation in environmental practices. Further, Läpple & Kelley (2015) also demonstrated the importance of interaction among farmers in driving the decisions of adopting environmental behaviors via spillover effects, a phenomenon also detected by Boncinelli et al. (2016). Additionally, studies showed that farmers' environmental behaviors could be influenced by farmers' relationships with neighboring farmers and their opinions on environmental behaviors farmers (Defrancesco et al., 2008) or because farmers share knowledge and information among themselves (Goulet, 2013). Ultimately, the interdependence in farmers' decision-making and behavior choices highlights the need to account for spatial autocorrelation of farmers' behaviors in policy formulation (Läpple & Kelley, 2015).

Spatial analysis

Typically, statistical analysis of spatial data assumes that the observations being studied reflect an outcome of a random process. As such, each observation is treated as just one of the possible outcomes, and the usual assumption is the assumption of Complete Spatial Randomness (CSR). Essentially, a process can be said to have CSR if it upholds two important assumptions. The first assumption is that every location in the area under study has the same chance to have a given characteristic or property (equal probability assumption). The second assumption holds that no dependencies exist between places (independence assumption) (Unwin, 2009).

But these two assumptions are not always sustained as deviations from CSR exist (Anselin & Li, 2019; Unwin, 2009). The deviations from CSR generally derive from two variations known as first-order and second-order variations. On the one hand, if certain observations are more likely to cluster in certain areas than in other areas, the assumption of equal probability is violated (first-order variations.) On the other hand, it may be possible for a process to generate a clustering in which the presence of one given observation at one location increases (or decreases) the likelihood of the presence of other observations in neighboring locations (second-order variation) (Unwin, 2009). In this study, for example, if a farmer at a given location intends to use improved cooking stoves to protect the environment, it increases the likelihood of his or her neighbors doing the same (second-order effects). These two scenarios of departure from CSR justify the use of spatial statistical analysis on data that have a spatial component to address the lack of randomness and independence among data. The spatial analysis explores and identifies associations over geographical space. The goal is to quantify the degree to which a value of a variable of interest at one location is dependent on the values of the same variable but at different locations (Cliff & J.K, 1981; Goodchild, 1986). When a given variable exhibits such dependence, it is said to have a spatial autocorrelation (Sokal & Oden, 1978). There exist several statistics to quantify spatial autocorrelation both globally and locally.

Global indicators of spatial autocorrelation provide a measure for the entire area of interest with the assumption of spatial stationarity; that is, the mean and variance do not change across the area of interest (Llyod, 2010; Naimi et al., 2019). Local indicators of spatial autocorrelation, on the other hand, allow the exploration of local patterns and spatial associations (Llyod, 2010). Research in spatial analysis has provided several local indicators for spatial autocorrelation. For example, (Anselin, 1995) introduced the Local Indicators of Spatial Associations (LISA), a set of statistics that deconstruct the global measure and provide each location's contribution to the global measure. These local measures include local Moran's I and local Geary's c statistics, and their purpose is to assess whether local spatial clustering of similar values around a given observation is significantly different from the global mean. Other local statistics, Gi and G*I, were also introduced to allow the detection of local pockets of spatial associations that would be otherwise difficult to detect with global statistics. They indicate local clustering of low and high values (Getis & Ord, 2010; Ord & Getis, 1995).

Objectives of the study

To date, no studies have explored spatial patterns of environmental behaviors in Rwanda or the Musanze district in particular. This study examines spatial patterns of farmers' behavioral intent across the study area by using spatial analysis techniques. This study employs spatial analysis techniques on data collected from farmers in Rwanda to explore spatial patterns of behavioral intent to engage in environmental behaviors. The study further maps spatial patterns to assess similarities or differences in behavioral intent variables and detect areas where these similarities or differences are concentrated. More specifically, the study seeks to:

- Test the spatial autocorrelation in variables related to farmers' environmental behaviors,
- Perform exploratory spatial data analysis for spatially autocorrelated variables to identify and map spatial clusters.

The study hypothesizes that behavioral intent in the study area is spatially autocorrelated. That is, the behavioral intent of a given farmer may be influenced by his or her neighbor's behavioral intent. Thus, distinguishable areas of concentration (clusters) of behavioral intent may be present in some areas within the study area. Results from this study provide a further understanding of farmers' environmental behaviors and intentions in the district of Musanze. In particular, by adding the spatial aspect to farmers' environmental behavior analysis, the findings of the study have implications on natural resource management as it may suggest geographical areas that present opportunities or challenges for specific environmental management initiatives.

Materials and Methods

Study area

This study was undertaken in the Musanze district, one of the five districts of the northern province of Rwanda. The surface area of the Musanze district is about 530 km^2 (200 sq mi), with 368,000 people and a population density of 694/km^2 (1,900/sq mi). Musanze population represents 3.9% of the total population of Rwanda and 21.3 % of the Northern Province population (MINECOFIN, 2015; NISR, 2013). The district comprises 15 administrative sectors, 68 cells, and 432 villages. Around 72% of the resident population live in rural areas, making the district of Musanze largely rural (MINECOFIN, 2015). With the majority of volcanoes being located within the district, Musanze district is the most mountainous district in Rwanda. These volcanoes are home to mountain gorillas, making Musanze a tourist destination (Rwanda Convention Bureau, 2021; Volcanoes National Park, 2021).

Sampling

A two-stage cluster sampling was employed to select respondents. Usually, multi-stage sampling, such as a two-stage sampling, is used when it is difficult to obtain a sampling frame or when the population is scattered over a wide geographical area (Chauvet, 2015) as was the case for the Musanze district. Another motivation to use cluster sampling was to reduce cost since this technique uses fewer resources unlike other sampling techniques (Legg & Fuller, 2009). For this study, the procedure consisted of three main steps: defining the frame, selecting the clusters from the frame, and finally selecting the respondents from the clusters. The first step was to define the sampling frame, i.e, obtaining a list of elements of the population to be sampled. The area sampling frame was chosen as it is very common and has the benefit of reduced travel costs (Gambino & do Nascimento Silva, 2009) and complete coverage of the targeted geographical area (Nusser & House, 2009). The area sampling frame was the geographical area of the Musanze district was considered an area frame and was divided into mutually exclusive sectors (clusters.) The first stage of the two-stage clustering involved the random selection of mutually exclusive clusters from the frame. Ultimately, the study area (Figure 1) consisted of 7 sectors as our clusters: Busogo, Gacaca, Gashaki, Kinigi, Nkotsi, Nyange, and Shingiro.

In the second stage of a two-stage cluster sampling, data were collected from randomly selected respondents in each cluster. Once in the selected sectors, a random household was picked to start with. Generally, a random spot along the main road or street would be picked and the data enumerators would go in four different directions. Every enumerator would pick a random house to start with, and then would skip a few houses and pick another household until someone to interview was found. This was not a systematic selection as it did not follow any consistent number of houses before picking the next; enumerators just walked a few meters and tried a few households until the person to interview was found. Ultimately, 604 responses were collected overall from the study area (Figure 3-1).

Instrumentation

Structured interviews were used to collect information on environmental behaviors and their factors. The questionnaire used in this study was adapted from the standard guide recommended by Fishbein & Ajzen (2010) in their book on Reasoned Action Approach (RAA) to understanding and predicting behavior (see its Appendix – Constructing a Reasoned Action Questionnaire, page 449) in addition to the questionnaires typically used in testing the Theory of Planned Behavior. In the context of environmental behaviors, this type of measurement has been implemented in various studies such as studies by Fornara et al. (2011), Passafaro et al. (2019), Farani et al., (2019), and de Leeuw et al. (2015).

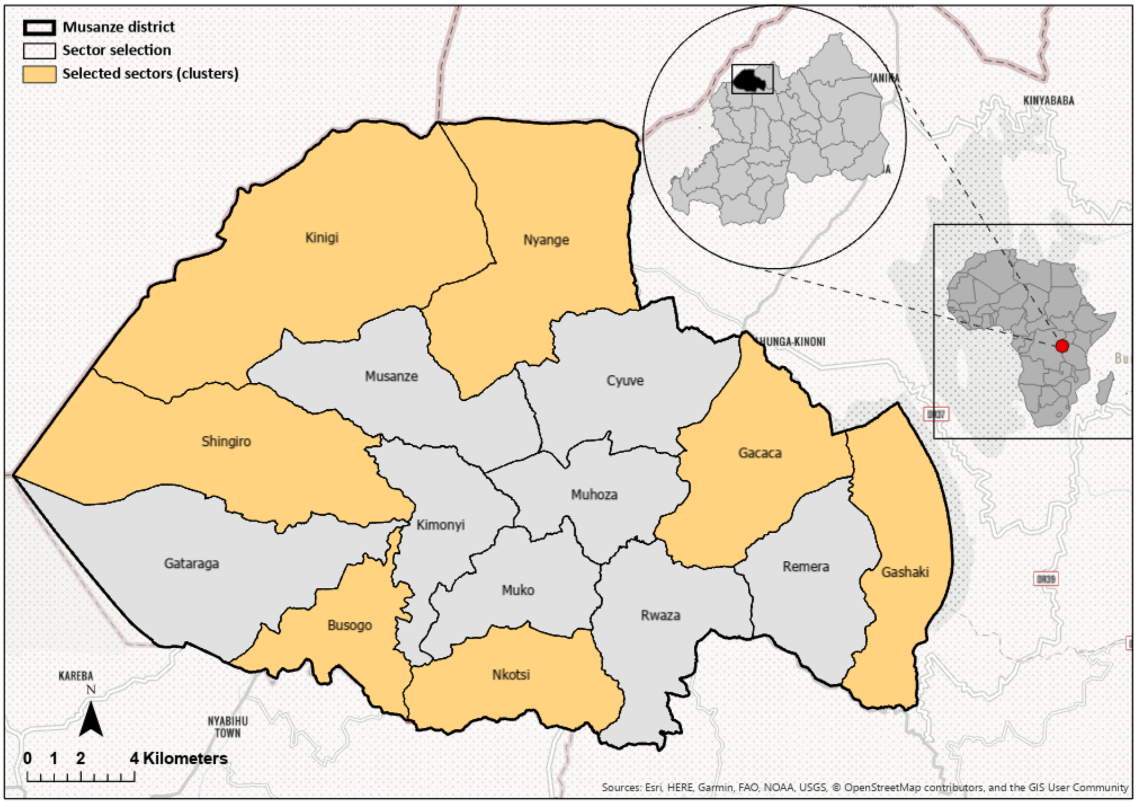

Figure 3-1: Study area, Musanze district, northern Rwanda

Description of the instrument

This study measured the central factor of behavior: behavioral intent; i.e., the intention to engage in environmental behaviors (Ajzen, 2012). Behavioral intent was measured using 10 items (see G section in the questionnaire). Respondents were asked to answer pairs of questions for each environmental behavior. The first question in each pair was a binary (Yes/No) question about whether or not they were intending to engage in a given environmental behavior (sample item: "During the next rainy season, do you intend to harvest rainwater to increase water quantity in your household?"). Related to the first question, the second question of each pair was about the degree to which respondents were decided to engage in the chosen environmental behavior (sample item: "To what degree are you decided or undecided to harvest rainwater to increase water quantity in your household in the next rainy season?"). Responses options for the second question were rated on a 5-point Likert scale ranging from 1 (Very undecided) to 5 (Very decided).

Ethical approval

Data collection was approved by the Internal Review Board (IRB) at the University of Tennessee, Knoxville (IRB number: UTK IRB-21-06216-XM IRB). To obtain the approval letter, an informed consent form, an alternative[11] training material used to train enumerators, and an individual investigator agreement, a cultural appropriateness letter from the local authorities in Rwanda were submitted to IRB.

Data collection

Data were collected by administering a survey to randomly selected farmers in the Musanze district between July and August of 2021. The questions were loaded into the iSurvey (version 2.14.32) and DroidSurvey (version 2.9.3) software, two versions of the same data collection tool operated by HarvestYourData[12], a mobile survey software. Using these tools, data were collected offline during the day and were uploaded onto the HarvestYourData database at the end of each day of data collection. In total, 4 devices (3 iPads and 1 tablet) were used to collect data.

The questionnaire had 8 sections of questions, each with its theme: (1) screening questions, (2) natural resources management, (3) environmental behaviors, (4) attitudes, (5) subjective norms, (6) perceived behavioral control, (7) intention, and (8) socioeconomics. In addition to these questions, geographical location data (latitude and longitude) were gathered for spatial data analysis. To do that, this study used the Global Positioning System (GPS) and

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[11] The alternative training was used so that enumerators did not have to complete the online CITI training as that could have posed a challenge to do. Alternatively, a training module was developed and adapted from an alternative CITI training compiled by a UTIA research team that did a research in Rwanda and approved by UTK IRB in 2017. The training module was submitted as part of the IRB application for this study and was approved.

[12] Address for the HarvestYourData: www.harvestyourdata.com; address: 3 Kaitawa Road York Bay Lower Hutt New Zealand

location services embedded in the iPads and Tablets used during data collection. On average, each survey took between 15 and 20 minutes to complete. After the survey, each participant was thanked for their participation and was asked if they had any comments or questions they had before closing.

Data analysis and spatial techniques

Spatial autocorrelation and spatial dependence

As suggested by the first law of geography (Tobler, 1979), the spatial arrangement may result in a spatial component in observed data, thus resulting in neighboring locations having more similar values. This spatial arrangement results in the presence of systematic spatial variation in a given variable, which is known as spatial autocorrelation. A positive spatial autocorrelation derives from neighboring observations having similar values whereas a negative one derives from neighboring observations having dissimilar or contrasting values (Haining, 2001). The degree of spatial autocorrelation is referred to as spatial dependence (Crawford, 2009). To assess the presence of spatial dependence, certain tests must be conducted. Tests can be global or local.

Global measures of spatial autocorrelation provide a single measure of spatial dependence (Crawford, 2009). Thus, global measures of spatial autocorrelation provide a measure for the entire area of interest with the assumption of spatial stationarity; that is, the mean and variance do not change across the area of interest (Llyod, 2010; Naimi et al., 2019). The most common global spatial autocorrelation test is the Moran's I (Moran, 1948) statistic, followed by Geary's c (Geary, 1954). Moran's I describes spatial association by focusing on the covariance of the variable whereas Geary's focuses on the difference (e.g., squared difference) that exists between locations (Wu & Kemp, 2019).

In contrast to global measures, local measures yield spatial dependence as measured at multiple locations across the area of interest (Crawford, 2009). These local measures allow the exploration of local patterns and spatial associations (Llyod, 2010). There are several local measures for spatial autocorrelation. For example, (Anselin, 1995) introduced the Local Indicators of Spatial Associations (LISA), a set of statistics that deconstruct the global measure and provide each location's contribution to the global measure. These local measures include local Moran's I and local Geary's c statistics, which assess whether local spatial clustering of similar values around a given observation is significantly different from the global mean. Other local statistics, such as Gi and G*I, were introduced to allow the detection of local pockets of spatial associations that would be otherwise difficult to detect with global statistics. They indicate local clustering of low and high values (Getis & Ord, 2010; Ord & Getis, 1995).

All these measures are usually suitable for continuous data, and as a consequence, do not apply to categorical and binary data. When data are not continuous, it becomes a challenge to assess the local spatial association of variables of interest. Examples of these instances include cases where data are binary or categorical with more than 2 categories. In this study, for example, behavioral intent was measured by a binary question – that is, whether or not respondents intended to engage in a given behavior. Given the binary nature of this variable, relying on traditional LISA methods (such as local Moran's I) would not have been appropriate for this study.

Measures of spatial autocorrelation for binary and categorical data were proposed for global and local indicators. For binary data, the choice for a global measure of spatial association is the join count statistic as introduced by Dacey (1965) and generalized by Cliff & Ord (1973). Each unit is coded as 0 or 1, and the statistic derives from counting the neighboring units with their value pairs. As such, the three possible pairs are the 1-1 pair (known as BB joins), the 0-0 pair (known as WW joins), and the 0-1 pair (known as BW joins). While the latter pair indicates a negative spatial autocorrelation, the former two denote a positive spatial autocorrelation (Anselin & Li, 2019; Wong & Wang, 2018). Among these possibilities, the global join count statistic focuses on the BB joins, where the number of observations of the occurrence of interest (1 in this case) is much less than half of the sample. Formally, if variable x_i is at location *i* with 1 or 0 as the value, the global join count statistic can be written as:

$$BB = \sum_{i} \sum_{j} w_{ij} x_i x_j$$

where w_{ij} denotes the elements of a binary spatial weights matrix whose purpose is to specify the locations of *i* and *j*. This formula of BB join count statistic was used to determine the presence or absence of global spatial autocorrelation for behavioral intent to engage in various environmental behaviors. To accomplish this task, the the R (R Core Team, 2013), a software for statistical programming. Statistically significant variables suggested that there was a global spatial autocorrelation in the variable of interest. As this measure identifies the global spatial association, it does not reveal the local variation. As a consequence, variables that were significant in the global measure were further used to test local spatial association.

To identify the local patterns of spatial association, the local version of the BB join count was used. The local version of the global BB join count statistic was introduced by (Anselin & Li, 2019) following Anselin (1995)'s Local Indicators of Spatial Association (LISA). The formal representation of the local BB join count statistic can be written as:

$$\mathrm{BB}_i = x_i \sum_{j} w_{ij} x_j$$

where w_{ij} represents the elements of a binary spatial weights matrix and $x_{i,j}$ can only take on the values of 1 and 0. To represent the weights, a distance-based matrix was used for every variable of interest, with 1 representing the intention to engage in a given behavior and 0 otherwise. The local BB join count statistics were estimated using the GeoDa™ 1.14.0 software, particularly the Univariate Local Join Count option. Inference in local join count statistic can be done either through hypergeometric distribution or a permutation method. Anselin & Li (2019) and Anselin (1995) recommend the permutation approach in which a pseudo p-value is computed. For point locations where x_i=1, the idea is to perform several random permutations of the rest of the observations and count neighbors whose x_j=1 is equal to or greater than the observed value of the join counts. The default permutation of 999 was used to run the univariate local join count statistic for this study. This approach is a one-sided hypothesis test against the null hypothesis of spatial randomness. Only statistically significant observations ($p \leq 0.05$ or lower) were retained to show clusters where the spatial association was significant.

Results

The study collected data from 604 respondents in total. However, the spatial analysis used data on observations with geo-referenced information. The total number of geo-referenced observations was 566. The point locations are shown in Figure 3-2. On average farmers have around 17 neighbors (Figure 3-3). The highest number of neighbors that a farmer has is 36 whereas the lowest number of neighbors is 1.

Global spatial autocorrelation

Results from the global join count statistics analysis (Table 3-1) indicate that three variables of behavioral intent were significant. This significance suggests that these variables exhibit global spatial autocorrelation. These variables are behavioral intent to (1) use improved cooking stoves, (2) use pellets, and (3) use LPG gas as a source of fuel for domestic cooking.

Local spatial autocorrelation

For each variable of behavioral intent, the univariate local join count statistic was computed and its significance was assessed with 999 permutations. The locations where the pseudo p-value was 0.05 or smaller are shown in significance maps. The identified locations on the significance map represent the clusters of a 1, which is surrounded by more neighbors with 1 than would be the case under spatial randomness. Consequently, there exists no distinction between high-high and low-low since high-high is the only valid notion for a cluster of a binary variable (Anselin & Li, 2019). The significance maps for variables whose local join count statistic proved significant were produced.

The resulting maps of significance indicated various regions within the district where there were clusters of spatial association for different variables. Figure 3-4 indicates that only two locations in the southwestern part of the district (in Busogo sector) exhibit a significant spatial clustering for the use of pellets.

Figure 3-5 reveals that spatial clustering for the use of improved cooking stoves for domestic cooking is present across the study area in 161 locations. Furthermore, different regions within the study area exhibit varying degrees of spatial clustering. Although there seem to be clusters of spatial association across the entire area of study, Shingiro sector (in the eastern part of the Musanze district) has the majority of clusters with the highest significance of spatial autocorrelation (p=0.001).

Figure 3-6 shows that only three clusters can be identified for the use of LPG gas for domestic cooking. They are 11 locations in total.

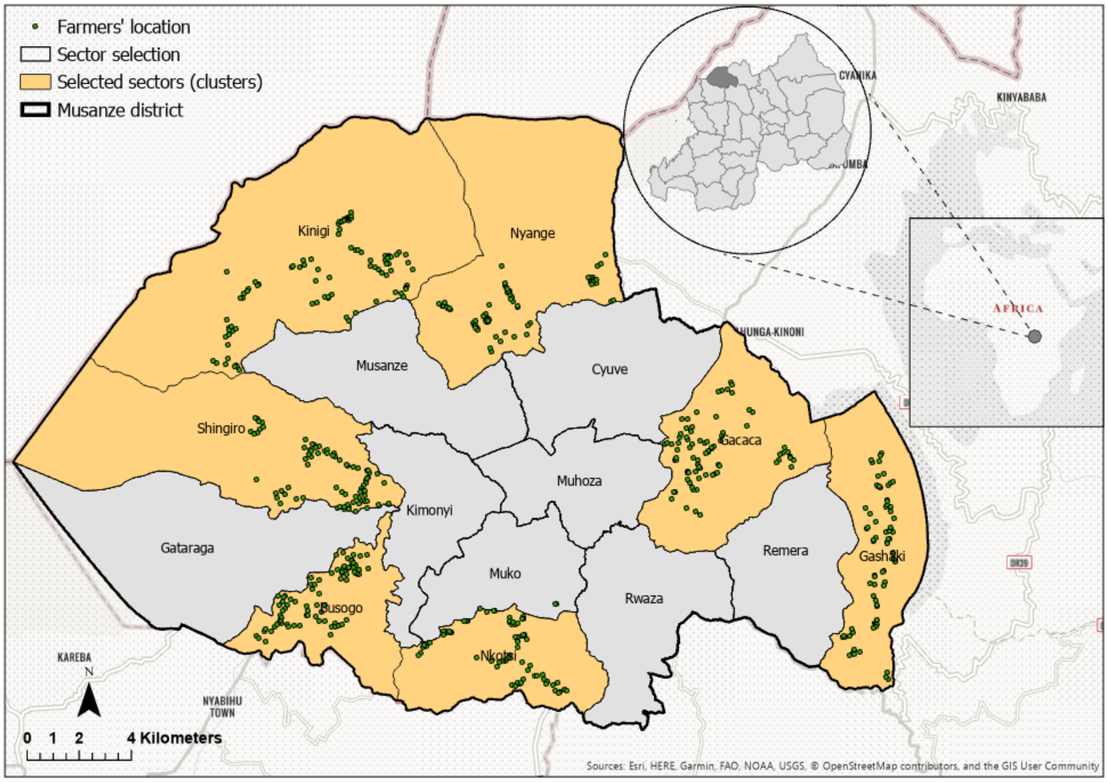

Figure 3-2: Point locations in Musanze district — 2021

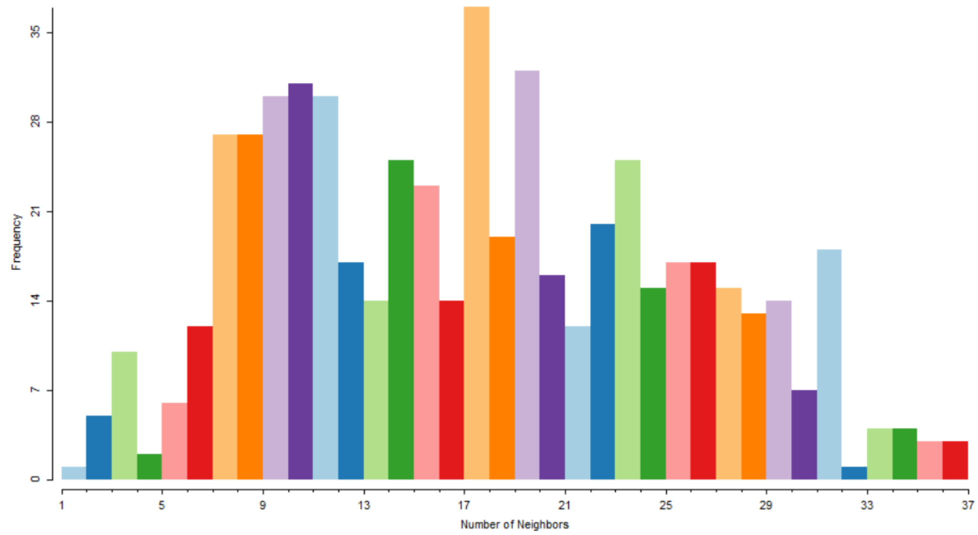

Figure 3-3: Number of neighbors for respondents (n=566) in Musanze District, 2021

Table 3-1: Description and significance of global spatial autocorrelation of behavioral intent to engage in environmental behaviors among farmers (n=566) in Musanze district, northern Rwanda, 2021

Variable	Description	Spatial autocorrelation (p-value)
intention_rainwater	Behavioral intent to harvest rainwater	0.116
intention_fertilizer	Behavioral intent to use organic fertilizer	0.345
intention_stoves	Behavioral intent to use improved cooking stoves for domestic cooking	0.00***
intention_pellets	Behavioral intent to use pellets for domestic cooking	0.017*
intention_lpg_gas	Behavioral intent to use LPG gas for domestic cooking	0.001**

**p < .05; **p < .01; ***p < .001*

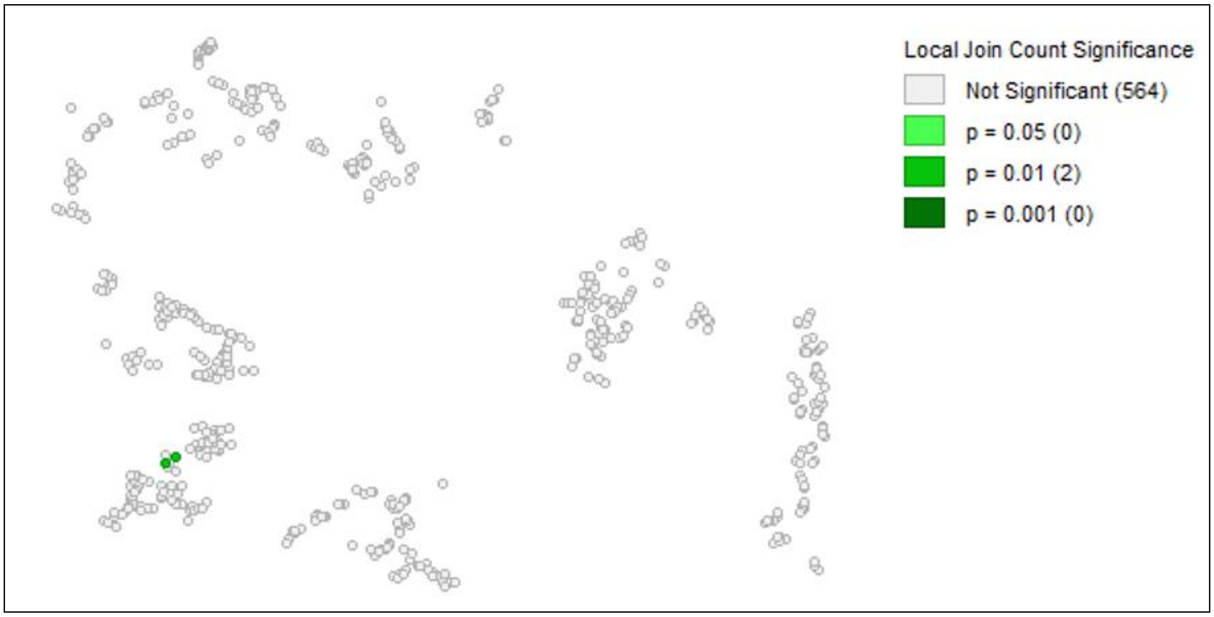

Figure 3-4: Significant univariate local join count locations for the use of pellets - 2021

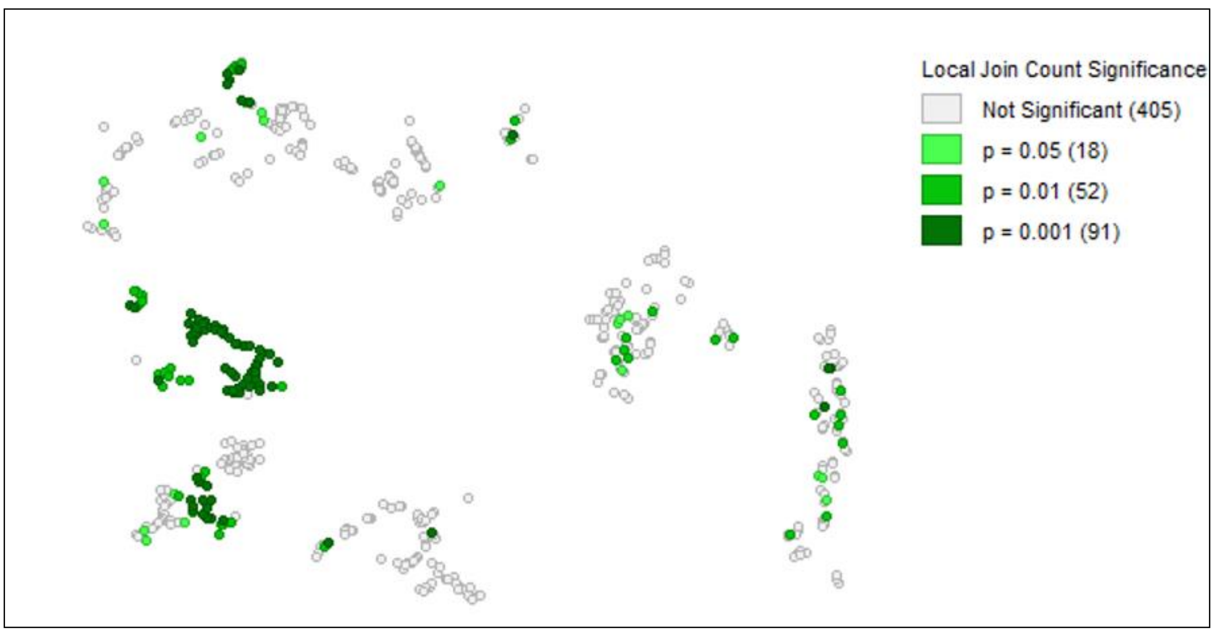

Figure 3-5: Significant univariate local join count locations for the use of improved cooking stoves - 2021

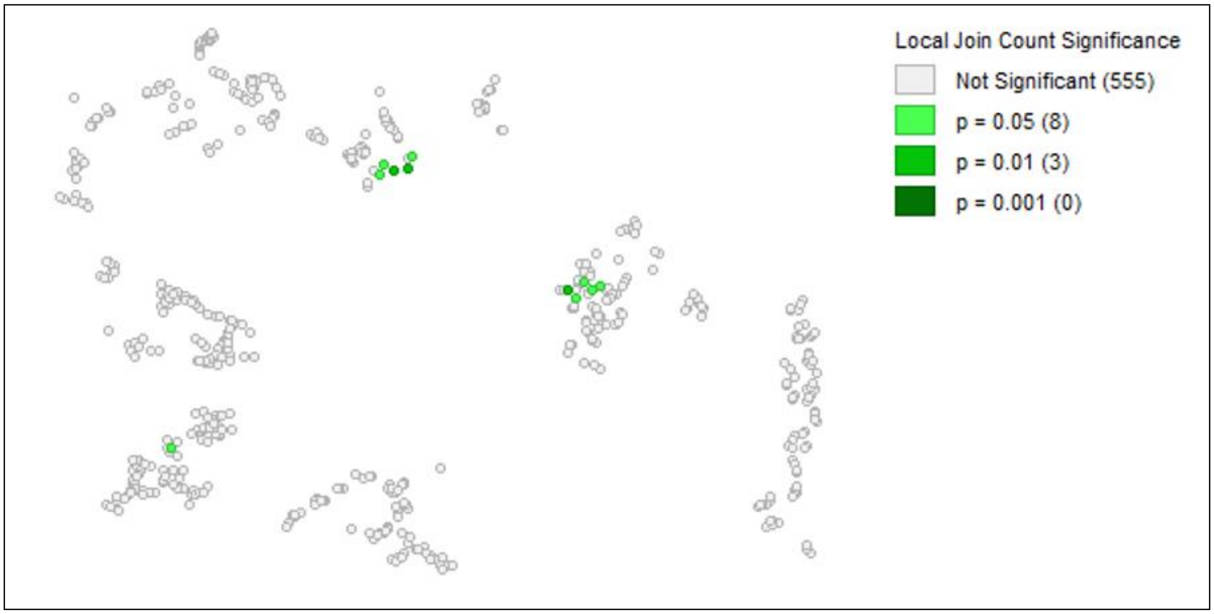

Figure 3-6: Significant univariate local join count locations for the use of LPG gas - 2021

Discussion of the Results

Overall, only three variables proved to have clusters where the spatial association was significant. The significant spatial association for these variables suggests that farmers at these locations are not randomly distributed, but are spatially clustered.

These findings align with other research work that demonstrated the importance of spatial association in explaining environmental behaviors. For example, Läpple & Kelley (2015) found that farmers who lived in close proximity exhibited similar behaviors. Similarly, Schmidtner et al. (2012) found that organic farming activities were more likely to occur in regions that were close to other regions with high shares of organic farming activities. Several other studies have demonstrated the importance of spatial autocorrelation in farmers' environmental behaviors (Boncinelli et al., 2016; Liu et al., 2020; Yang et al., 2014).

These findings support the notion that spatial patterns in farmers' environmental behaviors could be driven by social interactions. This notion is consistent with other research on spatial analysis of farmers' environmental behaviors. For example, in addition to finding regional clustering in farmers' participation in environmental behaviors, Boncinelli et al. (2016) observed that one reason for the diffusion of farmers' participation could be the imitation process. Similarly, Läpple & Kelley (2015) showed the importance of interaction among farmers in driving the decisions of adopting environmental behaviors through spillover effects. The effect of information spillover was also detected by Boncinelli et al. (2016). Lastly, farmers were found to adopt environmental behaviors because of their relationships with neighboring farmers and their opinions on environmental behaviors (Defrancesco et al., 2008) or because of knowledge sharing among farmers (Goulet, 2013).

Local indicators of the spatial analysis indicated that three variables in particular exhibited spatial dependence. These are behavioral intent to use pellets, behavioral intent to use the improved cooking stoves, and behavioral intent to use LPG gas. With regards to the use of pellets, as shown by the results, almost all variables did not exhibit any spatial dependence except for only two location points. These locations are located in Busogo sector (Figure 3-4), thus indicating that these farmers are less likely to intend to use pellets for domestic cooking by chance. The presence of only two data points with significant spatial associations could mean that social interactions may not be as effective in influencing farmers to undertake the use of pellets as an alternative source of energy for domestic cooking.

Regarding improved cooking stoves, results (Figure 3-5) revealed the presence of spatial clustering for the use of improved cooking stoves for domestic cooking across the study area at 161 point locations. Furthermore, different regions within the study area exhibit varying degrees of spatial clustering. Although there seem to be clusters of spatial association across the entire area of study, Shingiro sector has the majority of clusters of significant spatial autocorrelation, followed by Busogo sector (both in the western part of the Musanze district). This finding suggests that every farmer in these locations who intends to use improved cooking stoves has more neighbors who intend to do the same than would be expected under spatial randomness situations. This finding could also suggest that there might be more social interactions among farmers in the study area which could lead to farmers' intention to undertake the use of improved cooking stoves.

Three clusters were identified concerning the use of LPG gas with 11 location points in total. These clusters are located in the east, north, and west of the district – in the sectors of Gacaca, Nyange, and Busogo. Like in the case of the use of other sources of energy, the use of

LPG gas suggests the possible effect of interactions among farmers which could increase the likelihood of farmers’ intention to undertake the use of LPG gas.

Overall, variables that exhibited spatial dependence were related to energy. This finding is consistent with findings from Zhao et al. (2021) that showed spatial dependence in the distribution of energy consumption practices. Furthermore, regarding the intention to engage in energy-related behaviors among farmers, spatial autocorrelation was detected in farmers’ intention to adopt alternative sources of energy in other studies. For example, Skevas et al. (2018) found spatial autocorrelation in farmers’ intentions to avail their land for bioenergy crop production. Additionally, the study revealed that the detected spatial dependence resulted from the intentions of farmers’ neighbors and spillover effects. Similarly, a study by Yu et al. (2021) revealed that farmers’ adoption of green control techniques, which include energy-saving, was spatially correlated, and clusters were identified in the distribution.

The study’s results have implications on policy and strategy design for environmental protection programs. For example, by identifying regions where social interactions – and thus spatial associations) – are more likely to influence farmers’ environmental behaviors, natural resource authorities in Rwanda can design programs that are better suited for those areas. This strategy can increase the effectiveness of natural resource policies among farmers, thus improving the uptake of environmental measures. As argued by Yang et al. (2014), targeting specific and designated regions can increase the effectiveness of environmental policies. Findings from Schmidtner et al. (2012) also suggest that possible policy implications could include focusing certain environmental practices on specific areas. In the case of this study, it can be suggested that farmers who live in Shingiro sector are more likely to adopt these programs that promote the use of improved cooking stoves than farmers in other areas.

Furthermore, given the possible social interactions that may exist in areas with significant spatial dependence, policies that promote the use of energy-saving practices among farmers should not assume independent farmers’ behavior but account for spatial interactions among neighboring farmers. As such, programs and policies that aim at farmers' networks rather than individual farmers are more likely to be effective in addressing the challenges of the adoption of energy-saving technologies. Other studies made similar remarks including Skevas et al. (2018) and Tirkaso & Hailu (2022).

Conclusions

This study explored the spatial aspects of farmers’ environmental behavior, in particular, the behavioral intention to engage in environmental behaviors. Specifically, the study focused on behavioral intent to harvest rainwater, use organic fertilizer, and use alternative sources of energy for domestic cooking, namely pellets, improved cooking stoves, and LPG gas. The justification for the study was that possible social interactions can explain the spatial distribution of intention to undertake environmental behaviors.

This study employed both global and local join count statistic to detect clusters of spatial association globally and locally. Results revealed that only variables that relate to alternative sources of energy exhibited a global spatial autocorrelation. Further, local measures of spatial association revealed that clusters in certain regions had a significant spatial association. The significant spatial association for these variables implies that farmers at these locations are not randomly distributed, but are spatially clustered. As argued in this study and supported by other research work, the spatial clusters could be driven by social interactions and spillover effects.

However, further research could ascertain the link between the spatial distribution found and farmers' behavioral intention.

These findings have implications for further understanding the spatial aspects of environmental behaviors among farmers in Rwanda, the Musanze district in particular. By confirming the presence of spatial autocorrelation in certain locations, this study suggests that farmers in some areas are more likely to have similar intentions to engage in particular environmental behaviors than farmers who live in different area. This observation can provide useful insights for natural resources practitioners as it may suggest areas that present opportunities or challenges for environmental management initiatives. Furthermore, agricultural programs and strategies should, on the one hand, consider global spatial dependence, but, on the other, account for local heterogeneity in designing specific strategies for each area of interest.

Lastly, the methods employed in this study are exploratory. As such, they only offer an exploratory account of behavioral intent among farmers. A further analysis that combines spatial analysis and statistical modeling would be a good subject for further research.

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CONCLUSION

This research explored human dimensions of natural resources among farmers in Musanze district. Overall, the study investigated farmers' perceptions of their consumption natural resources (water and charcoal). The goal was to understand whether farmers perceive that their natural resource consumption has changed or not and to what extent. Results indicated that farmers perceive that their consumption of natural resources has changed. Further, the study revealed some of the factors that play a role in farmers' perceptions of their natural resource consumption. It is worth acknowledging that caution should be exercised in interpreting the results as overestimation or underestimation of natural resource consumption can occur. Thus, although results indicated that the consumption of natural resources has increased, the conclusion on whether actual consumption has increased will require further investigation. Future studies can further assess whether the actual consumption of natural resources has changed and the factors that influence that change. Furthermore, although the majority of farmers feel that their consumption of resources has increased since the project started, it is crucial to note that there might be many factors that may have contributed to the increased consumption of resources; some may be related to the project while others may not be related to the project. Based on the results, one recommendation is that the management of natural resources should integrated into the design of food security projects such as the TI project.

In addition to perceptions, this research investigated environmental behaviors among farmers. The study employed the Theory of Planned Behavior (TPB) to examine the influence of attitudes, subjective norms, and perceived behavior control on farmers' behavioral intent to engage in environmental behavior behaviors. Specifically, the study focused on rainwater harvesting, the use of organic fertilizer, and the use of alternative sources of energy for domestic cooking. Overall, the study corroborated the notion that attitudes, subjective norms and perceived behavioral control exert an influence on farmers' behavioral intent. However, as results revealed, the influence of factors and the direction of the influence can vary depending on the behavior considered. Overall, the study provides insights that may guide programs and interventions that seek to promote environmental behaviors among farmers.

Given the importance of spatial proximity in explaining people's behaviors, this research examined the spatial patterns in environmental behaviors. The third article of this research discusses the spatial analysis of farmers' behavioral intent to engage in environmental behaviors. Specifically, this research focused on behavioral intent to harvest rainwater, use organic fertilizer, and the use of alternative sources of energy for domestic cooking, namely pellets, improved cooking stoves, and LPG gas. This study employed local join count statistic to detect clusters of spatial association. Results revealed that only variables that relate to alternative sources of energy exhibited a global spatial autocorrelation. Further, local measures of spatial association revealed clusters in certain regions with a significant spatial association. These findings have implications in further understanding the spatial aspects of environmental behaviors among farmers in Rwanda, Musanze district in particular. The methods employed in this study are exploratory. As such, they only offer an exploratory account of behavioral intent among farmers. A further analysis that combines spatial analysis and statistical modeling would be a good subject for further research.

VITA

Jean François Régis Nisengwe was born and raised in Kigali, Rwanda where he did his undergraduate studies in environmental science at the University of Rwanda. After his undergraduate degree, he came to the United States (US) as a MasterCard Foundation Scholar and completed his Master of Science in Natural Resources and Environmental Management and Policy at Michigan State University. After his Master's degree, Régis returned to Rwanda and worked with non-profit organizations and consulting firms involved in natural resources, food security, and agriculture. Régis came back to the US to pursue his Ph.D. in Natural Resources at the University of Tennessee where his work explored the interface of natural resources and food security. When he is not working or studying, he is mentoring young people or reading books.