SUSTAINING SUSTAINABLE FARMING: AN EVALUATION OF THE REASONED ACTION AND COMPREHENSIVE ACTION DETERMINATION FRAMEWORKS FOR PERSISTENCE

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ABSTRACT

Sustaining Sustainable Farming: An Evaluation of the Reasoned Action and Comprehensive Action Determination Frameworks for Persistence

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This paper investigates the persistence of agricultural practices funded by the California Department of Food and Agriculture's Office of Environmental Farming and Innovation (CDFA OEFI). The central inquiry revolves around determining the most effective behavior model for analyzing persistence, comparing the Reasoned Action Approach (RAA), Comprehensive Action Determination Model (CADM), and CADM augmented with structural variables. The study's methodology integrates literature review, analysis of OEFI-funded practices, and statistical modeling to assess persistence levels. Contrary to existing literature, our findings reveal significantly higher levels of persistence than anticipated. Moreover, through model comparison, CADM augmented with political economic variables emerges as the superior model for analyzing and predicting persistence in agricultural practices funded by CDFA OEFI. These results contribute to a deeper understanding of behavioral determinants in sustainable agricultural practices and offer insights into optimizing policy interventions for long-term practice adoption and environmental impact.

Keywords: best management practices, behavioral persistence, agricultural maintenance

TABLE OF CONTENTS

Page

LIST OF TABLES vii

LIST OF FIGURES viii

1. INTRODUCTION 1

2. LITERATURE REVIEW 7

2.1 Climate Change 7

2.1.1 Agriculture and Climate Change 8

2.2 Agriculture in California 13

2.3 Adapting Farms to Climate Change 17

2.3.1 Best Management Practices & Predictors 23

2.3.2 Persistence of BMP Maintenance 26

2.4 Predicting & Explaining Behavior 28

2.5 Political Economy & Structural Factors 34

2.6 Research Gap 36

3. METHODOLOGY 37

3.1 Study Population 38

3.1.1 Contact Information 41

3.1.2 Acquiring Unknown Mailing Addresses 41

3.2 Survey Design 46

3.2.1 Distribution 50

3.2.2 Data Archiving 51

3.2.3 Data Cleaning 52

3.3 Data analysis 53

4. ANALYSIS 56

4.1 Model Creation 58

4.1.1 Latent Variables 61

4.2 Modelling 64

4.3 Model Performance 67

5. DISCUSSION & CONCLUSION 71

5.1 Models 72
5.2 Contrasting persistence with adoption literature.... 77
5.3 Variables of note 81
5.4 Future Research 92
5.5 Limitations 94
5.6 Conclusion. 96

BIBLIOGRAPHY.. 98

APPENDICIES

A. HSP Survey 111
B. Coding Framework 139
C. Reclassification Code for Analysis Compatibility .. 142
D. Sample Regression Code 144

LIST OF TABLES

Table Page

1. CDFA-OEFI PROGRAM CHARACTERISTICS AND PRACTICES EVALUATED. †INCLUDED IN REGRESSION ANALYSIS FOR PERSISTENCE 38
2. SURVEY RESPONSE RATES. 39
3. MEAN VALUES OF FARM AND FARM MANAGER RESPONDENT CHARACTERISTICS FOR TOTAL SAMPLE AND BY PROGRAM..................................... 40
4. TRUE STUDY POPULATION AFTER DUPLICATE CHECKING 46
5. SAMPLE CONSTRUCT QUESTIONS 48
6. SAMPLE HSP QUESTIONS 49
7. COVER CROP QUESTIONS USED FOR LATENT VARIABLE CREATION. †INCLUDED IN CADM BUT NOT RAA 62
8. CRONBACH'S ALPHA BY MODEL AND PRACTICE........................ 64
9. LOGISTIC REGRESSION OUTPUT 66
10. PERSISTENCE AND ABANDONMENT RATES (%) OF OEFI-FUNDED PRACTICES. PRACTICE PERSISTENCE IS DEFINED BY AN AFFIRMATIVE RESPONSE TO THE SURVEY QUESTION "DO YOU INTEND TO USE THIS PRACTICE IN THE NEXT 12 MONTHS?" 72

LIST OF FIGURES

Figure Page

1. RAA MODEL CREATION 59
2. CADM MODEL CREATION 60
3. CADM + PE MODEL CREATION 60

Chapter

1. INTRODUCTION

The ramifications of increasing atmospheric greenhouse gasses (GHGs) are the most significant societal and ecological challenges humanity faces in the 21st century. Climate change consequences, including increased frequency of extreme weather events, increased pest and disease risk, loss of groundwater, and temperature increases, pose a substantial risk to the agricultural industry (Nelson et al., 2009). Agriculture is often the primary industry in rural communities—supporting social, economic, and cultural well-being—making the effects of climate change particularly threatening to farmers and the rural community which is home to nearly one in five Americans (Deller et al., 2003; US Census Bureau, 2017). While the agricultural sector is threatened by climate change, it is also a contributor through the transportation of crops, intensive soil cultivation, and the inputs often used by farmers to increase yields.

To combat these threats from—and contributions to—climate change, researchers established the climate-smart agriculture (CSA) framework which highlights integrating climate change concerns into the planning of agricultural strategies to avoid devastating outcomes for both the environment and farm systems (Lipper et al., 2014). CSA emphasizes sustainably increasing farm productivity, building capacity to deal with climate repercussions, and utilizing practices, technologies, or cultural knowledge to reduce agricultural emissions (Lipper et al., 2014). CSA borrows from traditional soil and water conservation practices but also integrates a large swath of traditional agriculture and technical practices including integrated cropping systems, agroforestry, reduced tillage, utilizing local varietals, and the use of alternative manure management practices (IAASTD, 2009). Collectively, these strategies—which historically have addressed environmental issues (primarily soil and water) but are increasingly being used to address climate change—are referred to as best management practices (BMPs).

The adoption of BMPs—such as cover crops to improve soil health—is widely regarded as the most effective way for farmers to create resilient farm systems (Akkari & Bryant, 2017; Anantha et al., 2021; Bishop et al., 2005; Kreiling et al., 2018; Veltman et al., 2021). Examples of BMPs include cover cropping, no-till, and drip irrigation, however, the BMP(s) for a given farm is context-dependent, based on crop type, farm location, current production practices, and projected climate changes (Gitau et al., 2004; Veith et al., 2004). BMP adoption is often costly, thus financial incentive programs and technical assistance are often employed to motivate practice adoption (Gillespie et al., 2007; Liu et al., 2018; Prokopy et al., 2019). Despite the availability of financial incentives, information dissemination from research institutions, and technical assistance, not all farmers choose to adopt BMPs.

A wide body of research has synthesized the findings relating to the adoption of BMPs (Baumgart-Getz et al., 2012; Liu et al., 2018; Prokopy et al., 2008, 2019; Rudnick et al., 2021; Wauters & Mathijs, 2014). While the specific mechanisms that drive adoption are context-dependent, prevailing themes in the literature point to farm size (and thus income), sources of trusted information, and environmental attitudes as being generally predictive (Prokopy et al., 2019). The more acreage a given operation covers, the more likely they are to adopt BMPs (Prokopy et al., 2019). Similarly, farm managers whose attitudes are found to be pro-environmental, are members of social circles where BMP adoption is the norm, or those who view themselves as knowledgeable about a practice or program are more likely to adopt BMPs (Liu et al., 2018; Prokopy et al., 2019). Farms that sought out information from technical assistance providers, universities, resource conservation districts or input dealers about practices or programs were also shown to be more likely to adopt practices (Baumgart-Getz et al., 2012; Prokopy et al., 2019). Interestingly, Baumgart-Getz and colleagues (2012), found that despite the high degree of information source heterogeneity, seeking out information, across studies, had a relatively high impact on adoption.

While factors influencing adoption are widely researched, the upkeep of practices is generally ignored in adoption studies. Traditional adoption research has focused on enrolling farmers in incentive programs, overlooking the maintenance of BMPs post-program, the assumption being upon the termination of a contract, farmers will maintain practices (Dayer et al., 2016). Reimer and colleagues (2014) call attention to how little consideration has gone into investigating the drivers of *disadoption* and the potentially harmful outcomes of one-sided research on adoption. To date, far less research has investigated practice maintenance and program re-enrollment (Dayer et al., 2018; Jackson-Smith et al., 2010; Kwasnicka et al., 2016; Mitani & Shimada, 2021; Swann & Richards, 2016). Overall, the drivers of persistence appear to be similar to those best suited to predicting adoption while also considering theories of habit forming (Dayer et al., 2018). Kwasnica and colleagues (2016) conducted a review of theoretical explanations for the maintenance of behavior change, highlighting 5 prevailing themes—maintenance motivation, self-regulation, resources, habit, and social influences—that can be used to predict persistence.

California's passage of the 2006 Global Warming Solutions Act (AB32)—which mandates a return to 1990 levels of emissions by 2020—facilitated public spending on GHG reduction. Approximately 10% of funds distributed from the Greenhouse Gas Reduction Fund have been budgeted for agricultural-based projects (California Air Resources Board, 2018). These funds fall under grants distributed by the California Department of Food and Agriculture (CDFA) in the form of irrigation upgrades, installation of dairy digesters, and solar panel expansion. As part of California's ambitious reduction goals, the purpose of these grants is to reduce GHGs, therefore the maintenance of these practices is paramount, particularly when remediation is directly budgeted into California's cap-and-trade program. This thesis investigates 8 years of adopted practice maintenance from the CDFA Office of Environmental Farm Innovation (OEFI) grants under the State Water Efficiency & Enhancement Program (SWEEP), Dairy Digester

Research & Development Program (DDRDP), Healthy Soils Program (HSP), and Alternative Manure Management Program (AMMP) to better understand models of behavior which can best predict practice persistence and, following the first assessment, pertinent variables that are particularly impactful for practice persistence.

Chapter

2. LITERATURE REVIEW

In this chapter, I begin by defining the problem of global climate change; its impacts on ecosystems, biological cycles, and the very food systems we rely on in a post-Fordist industrial society. Next, I discuss the direct and indirect effects that will pose issues for agriculture in the future. I will then discuss so-called “best management practices” and how they can aid in creating food systems that are more resilient to the aforementioned threats. Further, I will discuss the challenges in adopting practices and what social science has discovered as the best predictors of adoption. I then will explain California’s climate initiatives and how they have facilitated public funding of programs to adopt BMPs. Lastly, I discuss the implications of assumptions of CA state policy and the necessity of understanding BMP practice persistence.

2.1 Climate Change

The Intergovernmental Panel on Climate Change’s 2022 report brings together a series of facts especially elucidative of future climate change. Once again, it is found that future climate will be impacted by a combination of weather’s inherent variability, the influence of historic greenhouse gas (GHG) emissions, future GHG emissions, and the yet-to-be-fully understood positive and negative feedback loops inherent in a changing global climate system (IPCC, 2022). With high confidence, the IPCC finds that there will be widespread ecosystem degradation, loss of biodiversity, changes in ecosystem physiology, and impacts on the cryosphere and biospheres' ability to continue to sequester carbon. These impacts are particularly suited to impact water systems and security. Projected changes to the water systems include changes in the water cycle, water quality, changes to the cryosphere, increased droughts, and increased floods, all of which will impact energy production, urban water use, and agriculture. With regards to food systems, climate change will increase stress on an already struggling global food system, increasing instances of food insecurity, reducing nutritional quality, compromising food safety and increasing global malnutrition (IPCC, 2022; Laestadius & Wolfson, 2019).

2.1.1 Agriculture and Climate Change

Climate change is forecasted to significantly negatively affect the current agriculture production schema (Gornall et al., 2010; Nelson et al., 2009; Rosenzweig et al., 2014; Vermeulen et al., 2012). Although many studies focus on a particular aspect of climate change in specific locations, relatively few studies provide a global assessment. Utilizing global gridded crop models, Rosenzweig and colleagues (2014) found that there are strong negative effects from climate change, particularly at higher projected rates of warming and at lower latitudes. In a 2010 review Gornall and colleagues (2010), find that the literature reveals both direct and indirect effects on agriculture. The direct effects of climate change on agriculture are changes in mean climate, increased frequency of extreme weather events, higher variability of climate, more instances of droughts, and increased precipitation and flooding, while the indirect effects are increased pest and disease risks, changes in water availability, and sea level rise. Changes in mean temperature affect both producers and crops. In any particular location, farming practices have been influenced by the historic mean climate state, meaning that the cultural capital and physical infrastructure that have been developed may require modification to mitigate falling productivity (Gornall et al., 2010).

Direct impacts of climate change on agriculture are effects that disrupt the biological processes that cultivated plants have grown accustomed to. Instances of extreme weather (hail, heat waves, etc.), increased precipitation and increased flood risk all can directly damage crops both above ground through physical damage and below ground due to anoxic conditions and excess moisture (Rosenzweig et al., 2002). Furthermore, extreme weather events may prevent the operation of farm machinery leading to delayed planting and harvesting (Rosenzweig et al., 2002). While climate models project an increase in annual mean soil moisture content globally, across agricultural regions time spent under drought is projected to increase (Gornall et al., 2010). Plants are subjected to drought conditions when either the water supply to their roots is limited or the loss of water through transpiration is high. Drought conditions lead to reduced yield through stomatal closure to prevent transpiration—thus inhibiting photosynthesis—and through a reduction in nutrient availability as most nutrients are introduced to flora through roots along with water (Fahad et al., 2017). Drought further impairs growth by impairing mitosis and cell elongation (Hussain et al., 2008). Heat stress, similarly, influences various biological processes including scorching of plant material, reduced chlorophyll count, poor germination, growth inhibition, and reduced biomass accumulation, leading to a reduction in yield and thus profit for farmers (Fahad et al., 2017).

The indirect impacts of climate change on agriculture are those that are the result of climate-related feedback loops. Of great concern to agriculture are pests and pathogens—fauna that feed on cultivated crops and diseases that plague them. Agriculture, through its goal of providing a food source for the human population, has provided conditions conducive to the emergence and spread of pests and pathogens through crop domestication and agricultural intensification (Bernal & Medina, 2018). In particular, agricultural intensification, through its maximize yield mentality, has resulted in crops cultivated for fruiting bodies—whereas plants naturally optimize for a balance between fruiting bodies, root stock, and pest and disease resistance. In addition, the globalization of markets for plants and plant products has allowed pests and pathogens to permeate far beyond their native habitats, resulting in 10 to 28% of crop production lost to pests and pathogens annually (IPCC, 2021). Global tourism and a market for exotic plants additionally affect the movement of pests and pathogens as the movement of infested seeds, planting materials, soil, and plant propagations across borders pose a risk to biosecurity (IPCC, 2021). In an analysis of the factors by which we can simulate the impacts of climate Juroszek & von Tiedemann (2015) finds that a multitude of factors including evolutionary pathways, climate factors, farmer adaptation, and agroclimatic zones are used to simulate pathogen and pest risks under climate change finding in general that impacts will be greater at the end of the twenty-first century when the effects of climate change are fully realized. The previously discussed juxtaposed distribution of precipitation is also felicitous to the discussion of pests and pathogens as warmer and drier conditions favor insect disturbances while wetter conditions favor disturbances from pathogens (Seidl et al., 2017). In addition to increased biotic risks to the food system’s security, abiotic feedback loops impacting sea-level rise pose a risk to agriculture. Sea level rise threatens low-land agriculture such as cultivated river deltas where the projected sea-level rise can lead to inundation of land (Titus, 1990). Areas not directly affected by inundation are threatened through coastal erosion which can span kilometers inland from their original location and through an elevated sea which provides a basis for flooding during storms. Sea level rise can greatly affect coastal groundwater basins, particularly in over-drafted basins which lack sufficient flow to resist saltwater intrusion. Sea level rise will increase the average salinity in rivers, bays, wetlands, and of high concern, aquifers, which threaten endemic species as well as the irrigation efficacy of agriculture (Titus, 1990).

2.2 Agriculture in California

California is the United States' largest agricultural state, home to a wide range of agricultural operations including, but not limited to vineyards, nuts, fruits, and livestock. According to the California Department of Food and Agriculture, California is home to over 69,600 farms, spanning 24.3 million acres of pasture lands, rangelands irrigated cropland amounting to an agricultural GDP of around 49.1 billion dollars in 2021 (CDFA, 2021). Over a third of the United States' vegetables are grown in the state, some of which are only found in the fields of California. Many of the issues facing global agriculture are particularly amplified in California. Lobell and colleagues (2011) write an early paper that investigates the specific climatic changes in California that are most likely to impact the state's agriculture. Working through a historical framework analyzing indemnity and disaster data from 1993 to 2007, they find that a wide variety of extremes are affecting California agriculture. They find that cold extremes are becoming less frequent—and project this decrease in frequency to continue—and that, in contrast, heat waves are likely to occur with increasing frequency in the future. Additionally, they find that changes in heavy rainfall and flooding events, which are the costliest of damages overall in California agriculture, are less predictable and models often disagree on where projected trends will lead. However, the authors state this incertitude should not derogate from what is known about temperature extremes, which, too, poses a great threat to agricultural operations. Given the vast array of climatic zones in California, this lack of generalizability is to be expected. Adequate levels of precipitation and groundwater recharge are of great importance to agricultural productivity, and the authors stress that refining models on rainfall are important. Given that damages from frost events have historically been more detrimental to crop productivity, the relative decrease in frost events—provided that farmers can adapt systems to resist heat events—can reduce some of the threats from climate change.

More recently, Pathak and colleagues (2018) have conducted an extensive review of climate trends and California agriculture. The authors reiterate the prior conjecture that the range of biomes from desert to subarctic permafrost leads to an inconsistent projection of climate impacts. They find that California’s climate is influenced by the cold current running down the coast from Alaska and offshore winds which allow storms to push west and limit tropical storms that reach land. Additionally, the El Nino Southern Oscillation and Pacific Decadal Oscillation influence rain and snow experienced within the state. The authors generalize that warming trends are mostly clustered during summer, followed by spring and fall and that inland increases in mean temperature will be more prominent than in coastal regions. When analyzing precipitation models, they find that the high inter-annual variability of precipitation records makes water resource planning and management difficult and unique to the state. In general, however, they find that Northern California may experience higher annual rainfall and larger storm events, whereas Central and Southern California are expected to be 15-35% drier by 2100. The accumulation of the Sierra Nevada snowpack serves as a primary water source for watersheds across the state, with up to 80% of the state's precipitation coming from snow annually, the predicted 65% loss of snowpack in high warming scenarios is particularly of note. Heat waves (defined as exceeding the 99th percentile of the local summertime average) further are found to increase throughout the state, with coastal regions experiencing nighttime temperature increases and inland regions will experience daytime heat waves, though, the authors mention that the irrigation of agriculture during the heatwaves may provide a defense against said heatwaves. The authors further find that low stream flow and groundwater levels will lead to drought conditions, additionally, through the soil and vegetation drying out, the risk of wildfires can further damage productivity. Lastly, it is found that warmer environments will lead to early-season snow melt, which will both increase the odds of winter flooding and water scarcity in the summer.

Given the climactic change that is expected, it is well established that the majority of California crops will face yield declines (Hong et al., 2020; Kerr et al., 2018; Lee et al., 2011; Lobell et al., 2006; Lobell & Field, 2011). Lobell and colleagues (2006) studied the impact on 6 major perennial crops in California: wine and table grapes, almonds, oranges, walnuts, and avocados, finding that climate change is very likely to put downward pressure on yields. Similarly, Lee and colleagues (2011) in a simulation of crop productivity of alfalfa, cotton, maize, rice, sunflower, tomato, and wheat under current management conditions of California’s Central Valley found that crop yields were expected to negatively affect yields. Lobell & Field (2011), assess threats to 20 of California's most valuable perennial crops using LASSO and decision tree models finding an estimated 13% reduction of yield across states and counties, that no crops will benefit from climate change, and cherries unambiguously (across models) will be harmed by climate change. Kerr and colleagues (2018) discuss several obstacles to creating a comprehensive picture of how specialty crops will fare under future climatic conditions, including the diversity of specialty crops and their cultivation practices; the uncertainty of climate change impacts on water resources at a regional scale; the interaction of climate with other stressors such as pests and diseases; and uncertainties in adaptive capacity. Due to the inherent difficulties, they utilize spatial analysis to determine a net decrease in yields. Finally, Hong and colleagues' (2020) results suggest that ozone damage to perennial crops will result in decreased yields. Overall, the literature paints a distressing picture of the productivity of future California agriculture.

2.3 Adapting Farms to Climate Change

As mentioned by Kerr and colleagues (2018), one impediment to creating a wide-ranging model of the incongruent effects of climate on agricultural yields is the adaptive capacity of farms in the face of climate variability. Although farmers historically have chronically had to deal with uncertainty–particularly regarding weather and price patterns–market globalization and climate change are causing sources of uncertainty to become multifarious and rapidly changing. This impacts farmers' ability to plan ahead, necessitating what is known as adaptive capacity.

Agricultural adaptive capacity is a combination of human, physical, natural, financial, and capital factors that influence a given farm's ability to cope with and adapt to future uncertainty and changes. Due to the variability in the possession of the abovementioned factors, agricultural adaptive capacity can be distilled into three coexisting approaches profuse within the farm management literature (Darnhofer et al., 2010). These approaches are: 1) the engineering approach (e.g. technical intensification, industrial inputs), a positivist, reductionist, approach with mechanistic systems, working within atemporal timeframes with "one size fits all" solutions; 2) the farm systems approach (e.g. crop rotation, reduced/no-till) a similarly atemporal approach with the distinction of having some linear projection into the future that employs systems thinking and recognizes contextual differences between locations; and 3) the complex adaptive system (e.g. agroecology, regenerative agriculture), a system of ceaseless restructuring with co-evolution of various interconnected facets. Darnhofer and colleagues (2010) stress that while the different frameworks were developed concomitantly, they are all still found dispersed throughout contemporaneous research, policy, and practice.

At the core of the engineering philosophy are efficiency, consistency, and predictability; in practice, problems are identified, and technological solutions are developed to address said issues to achieve a specific goal such as yield. Fundamentally, the engineering approach entails beliefs that it can "design" an agricultural production system—transforming a naturally variable system into a reliable mechanized system with calculable outcomes. In the design of said systems, problems are addressed piecewise; pests are addressed with pesticides, weeds are addressed with herbicides, once diverse ecosystems are reduced to monoculture, nutrient deficiencies are addressed with fertilizing inputs, and crops are arranged in such a way to allow harvesting apparatuses to extract the desired outcome most efficiently. More recently, robotics, remote sensing, and even machine learning have been applied to farming in a bid to maximize profit (Saiz-Rubio & Rovira-Más, 2020). An underlying assumption behind the engineering approach is that there are no cascading effects of implementing one engineered practice on the system as a whole; similarly, farmers are viewed as *homo economicus*—rational actors who will logically come to conclude that the infinitely applicable approach should be implemented on their farms. This philosophy is reflected in the technification of agriculture in the 1970s, which failed to recognize the inherent degradation of coetaneous practices and existed within an environment of abundant water, cheap inputs, and government-controlled prices (Anderson, 2016; Lobao & Meyer, 2001).

The farm systems approach is differentiated from the engineering approach in that it recognizes the different physical and social capital of farmers, and thus views farms not as a system of equations to be optimized but, rather as a system in itself with heterogeneous and ecological actors. Technical assistance providers—non-governmental organizations, university researchers and Extension agents, and other organizations dedicated to providing farmers with agricultural assistance—have recognized that both bio-physical and socioeconomic components of a farm needed to be considered when making production system changes, and thus the usefulness of an interdisciplinary approach to the analysis of practices and system changes (Darnhofer et al., 2010; Prokopy et al., 2019). The farm systems approach, according to Darnhofer and colleagues (2010), views farm operators as those with individualized risk tolerances, desired lifestyles, and quality of life. The farm systems approach thus focuses on the interaction of all the parts of the farming systems, for example, the constitutive elements and the self-regulating ecological processes of the farm and how to account for them. Instead of stabilizing production environments to achieve high yields, varieties are selected for being robust in a wide range of conditions. Standardization across practitioners of the farm systems approach, in this view, is not seen as desirable, as farmers and consumers have different preferences.

As the environmental and social impacts of intensified farming operations have come to light, there have been calls to move toward farming in a way that is more sustainable. One such approach is the complex adaptive system, also known as regenerative agriculture or agroecology (Darnhofer et al., 2010). Current conceptualizations of regenerative agriculture first came into the Western lexicon during the late 1970s before gaining momentum in the 1980s when it was taken on as a research project of the Rodale Institute. Robert Rodale, the founder of the Rodale Institute, defined regenerative agriculture as a broad range of agricultural practices that apply techniques meant to increase the productivity of agriculture and reduce environmental harm through supporting land and soil's natural biological base. Some of these techniques include crop rotation, the integration of various forms of biological pest management, commonly referred to as integrated pest management, nitrogen fixation, and practices meant to integrate livestock raising with crop production through field rotation (Giller et al., 2021). After first emerging in the public discourse in the late 1970s and 1980s, regenerative agriculture slipped out of academic and public consciousness in the late 1990s, and although terms like "sustainable agriculture" and "organic agriculture" remained, these are not wholly synonymous. Regenerative agriculture began to significantly reemerge in literature and public media in the mid-2010s; however, there is a lack of consensus around its definition and attempts to draw distinctions between similar paradigms have drawn murky boundaries. Yet, one important distinction can be made regarding how the philosophy of regenerative agriculture extends other paradigms of traditional farming by emphasizing the interdependence of human and environmental systems for the development of socially and environmentally sustainable agriculture and thus goes "beyond organic because it [includes] changes in 'macrostructure' and 'social relevancy', and seeks to increase rather than decrease productive resources" (Giller et al., 2021, p. 14). Despite a lack of consensus, definitions of regenerative agriculture commonly identify practices that seek to restore soil health and reverse biodiversity loss while maintaining high productive capacity and increasing welfare as falling into that category. Their interpretation proves useful as it highlights the centrality of regenerative practices that restore soil health—of which carbon recapture and emission mitigation fall—to the biologically-informed restructuring of farm systems to affect local food, social, and environmental systems, and thus promote global sustainability, and mitigate the effects of climate change.

2.3.1 Best Management Practices & Predictors

Implementing strategies from one or more of the three adaptive capacity approaches to bolster resilience is referred to as the adoption of BMPs. The term BMP describes practices that are "best" in the context of the farm (given management resources, experience, likelihood of persistence, and comfort with the task) when compared to other pathways aiming to accomplish the same task. As mentioned above, adaptive capacity includes human, physical, natural, and financial capital, all of which vary amongst farms targeted for adopting BMPs, thus necessitating an investigation of factors that best predict the adoption of BMPs to better target farmers. The adoption of BMPs is well-studied (Baumgart-Getz et al., 2012; Liu et al., 2018; Prokopy et al., 2008, 2019; Roesch-McNally et al., 2017; Ulrich-Schad et al., 2017). In an early synthesis of the literature Prokopy and colleagues (2008), utilized a vote count methodology, reviewing articles authored from 1980-2005, finding that the majority of the literature focuses on soil, nutrient, and pest management issues, while few studies focused on water, landscape, and livestock management. They find “reliable” measures, those difficult to interpret differently than others (e.g., age, farm size, annual income, etc.), are prevalent throughout the literature, though, across studies, are inconsistent in their direction of influence. In an analysis of physical characteristics, having larger farms was widely found to be positively correlated with BMP adoption, as were years of education, capital and income, network, and availability of labor. Age is the only physical variable found modally to have a negative impact on adoption. When included, it is found that attitudes towards risk, the profitability of the practice, receiving adoption payments, and heritage all are positively associated with adoption. General environmental awareness and awareness of environmental consequences are found to have a positive correlation with adoption, as was knowledge of “general terms related to environmental quality”. The authors discuss the observation that much of the adoption literature contains variables related to the physical attributes of a farm (e.g., age, size, etc.) whereas very few studies measure attitudes and awareness; when these are included in models, authors often do not discuss the theoretical reason for their inclusion.

In 2012, Baumgart-Getz and colleagues aimed to expand upon Prokopy and colleagues (2008) by expanding the analysis from a vote count methodology to a statistical meta-analysis. While the vote count methodology—which simply votes positive, negative, or insignificant for each study and each variable—is easily interpretable, it lacks an awareness of the specific values attached to covariates in linear regression or the sample sizes and power of various studies. The results of Baumgart-Getz and colleagues (2012) concur with Prokopy and colleagues (2008) on the impacts of farm size, age, capital, and networking.

The authors stress that while farm size has a large influence in the adoption literature, what is considered a large or small farm varies both geographically and by the type of cultivation occurring. They additionally find that while a formal education is insignificant in the statistical methodology, extension training emerged as having a positive impact on farmer adoption. They further suggest that due to education's insignificance—even with a high number of studies (n = 77)—it should be excluded from further adoption research. The authors additionally find that capital is the best financial predictor of adoption, farming experience is broadly insignificant, and that information has high predictive power—especially due to its low heterogeneity across types of informational sources (e.g., extensions, technical assistance providers, resource conservation districts, seed dealers, etc.) and across studies.

2.3.2 Persistence of BMP Maintenance

As discussed, social scientists have explored why farmers engage in conservation activities. The majority of practice adoption happens through the cost-sharing of multiple groups (CDFA OEFI typically covers the full cost of the project) or through technical assistance from some agency (Huffman & Just, 1999). These programs typically have expiring timeframes (1-5 years) for payments for ecosystem services, or the assistance given. What is far less researched is what occurs after these programs end—herein: the persistence of conservation behavior. In a Journal of Soil and Water Conservation editorial Reimer and colleagues (2014) set out a research agenda for natural resource social sciences studying adoption behaviors; goal four decrees that future research should investigate long-term and permanent conservation behavior. In 2016, Swann & Richards published a literature review drawing attention to the lack of research on landowner conservation post-intervention. The literature review analyzed forty-two papers, only five of which utilized empirical evidence to discuss persistence outcomes. Dayer and colleagues (2018) expands upon the review finding three more empirical studies that discuss persistence; of the eight total empirical studies, seven measured intention and not actual persistence outcomes. The rates of persistence across practices were highly variable, some being reported as low as 31% (Johnson et al., 1997) or as high as 85% (Hayes, 2012; Jackson-Smith et al., 2010) depending on conservation program contracts and persistence outcome (Dayer et al., 2018). From the literature, it is evident that the type of persistence outcome is informative of the persistence rate (e.g. land retirement, planting practices, etc.). Jackson-Smith et al. (2010) is the only paper in the review that directly measures persistence outcomes empirically, relying on interviews and visual confirmation of practice maintenance of NRCS contracts. Overall, they find that 80% of implemented NRCS contracts persisted after implementation. They find that structural practices were more likely than management practices to be maintained; though planting, levelling, and clearing had the lowest rates of dropout post-implementation. Additionally, they find that programs that received cost-sharing were more likely to be maintained, as well as those that involve fencing, riparian area protection, and livestock waste management. Practices targeting crop production, irrigation, and pasture and grazing management were less likely to be maintained. Overall, less than one-half of management BMPs were actively being used while over 80% of structural ones were still in use. While Jackson-Smith and colleagues (2010) tallies the persistence outcomes of various NRCS contracts, what they fail to do is to attempt to explain *why* persistence occurs.

2.4 Predicting & Explaining Behavior

The lack of theory-grounded behavioral models in agriculture adoption research was originally critiqued in

Lockeretz (1990) and later emphasized in Reimer et al. (2012a) and Reimer et al. (2012b) which eventually spurred a sort of empirical revolution within the literature and the widespread adoption of Ajzen's 1991 theory of planned behavior. To explain why behavior occurs, applied social scientists turn to psychology; common theories used in applied research include Fishbein and Ajzen 2015’s theory of reasoned action or the reasoned action approach (TRA or RAA)(previously, the theory of planned behavior (Ajzen, 1991)), Rogers (2003)’s diffusion of innovation (DOI), Schwartz & Howard (1981)’s norm activation theory (NAT), and Stern & Dietz (1994)’s value belief norm theory (VBN). The most common of the abovementioned theoretical frameworks found in pro-environmental behavior research are TRA, NAT, and VBN (Klöckner, 2013). TRA assumes that behavior is determined by the intention to perform a behavior, which itself is a function of attitudes, subjective norms, and perceived behavioral control (Fishbein & Ajzen, 2015). Attitudes themselves are divided into instrumental and experiential attitudes, measuring the preference for the described behavior over an alternative. Subjective norms are the presumed expectations of people around the subject of behavior (the injunctive norm) influenced by the willingness to perform the behavior by the subject (the descriptive norm); in other words, the social pressure scaled by the resistance to the social pressure. Finally, perceived behavioral control measures are the presumption of a subject to enact a behavior (e.g. financial, technical, intellectual). Taken together TPB predicts that people will perform positive environmental actions if they hold positive environmental attitudes, if other people expect and support their engagement in the practice, and if they have the necessary means to perform the behavior (Ajzen, 1991). The theory of planned behavior is found widespread throughout the farm BMP adoption literature, it is, however, critiqued for its lack of a moral dimension and of particular relevance for this study, its lack of viability for repeated behavior (Klöckner & Blöbaum, 2010).

Whereas TPB is a general, single-instance behavior theory, norm activation theory was developed for repeated altruistic behavior, which in the context of environmental research is taken to be a pro-environmental behavior (Schwartz & Howard, 1981). This theory states that if an actor feels morally obligated to perform a behavior, then they will perform the behavior. This moral obligation is referred to as a norm, and the norm is activated by four conditions being met. First, the person must be made aware that there is a need for help, following this they are aware of the consequences this behavior would be for the said subject in need, third, the actor must accept responsibility for their actions, and finally, they must perceive themselves as capable of carrying out the action. This action is thus informed by the morals of the actor (thus a quasi-binary good-bad dichotomy) whereas TPB looks at behavior in a more neoclassic economic way of weighing the cost and benefits of the behavior (Ajzen, 1991; Schwartz & Howard, 1981). Finally, the value-belief-norm-theory (Stern & Dietz, 1994) is an attempt to generalize NAT to include beliefs and behavior. It assumes that the behavior is determined directly by personal norms, which are based on the NAT. Stern additionally assumes that these personal norms must be activated by the ascription of responsibility and awareness of consequences. However, he ranks them into a causal chain where awareness of consequences is a necessary prerequisite of the ascription of responsibility. VBN ascribes awareness of consequences to a general ecological worldview which includes beliefs that humans' pursuit of resources put the world in a state of disequilibrium concluding that humans should not dominate Earth. The theory, in essence, attributes personal norms to be a prerequisite to behavior and thus has the same issues as the relatively narrow focus of NAT (Klöckner, 2013).

While unrelated to the field of agriculture, Frey & Rogers (2014) write an early paper on environmental behavior persistence looking at household energy conservation post-intervention. Their work lays out various persistence pathways that help explain changes in pro-environmental behavior post-intervention. This article looks at a theory-based approach to the 'persistence pathways' to inform policymakers on how to structure treatments to allow behavior to persist. The four persistence pathways are building psychological habits, changing what and how people think, changing future costs, and harnessing external reinforcement. Building psychological habits involve making people associate certain behaviors in a certain time and environment. Changing what and how people think refers to an intervention which begins to frame said intervention in a different light than actors originally associated themselves with (e.g. biking to work makes you believe you are a "bike person"). This can involve a conversing with the values of a farmer and highlighting their care for the land, so they believe they are now a conservationist and thus persist in using cover crops. Changing future cost refers to an intervention that changes how the practice can be maintained in the future. This can be the setting up of a compost system so that a farmer does not need to invest the money to compost themselves. Finally, practice reinforcement, such as support from an RCD or other information-giving entity can motivate persistence. The concept of persistence pathways is later generalized by Kwasnicka and colleagues (2016) and adopted to agricultural contexts by Dayer and colleagues (2018).

Due to the often-conflicting theories present in the behavior research sphere attempts to create a harmonious theory have been made by the likes of Fishbein & Ajzen (who claim many of the extraneous constructs can be fit within their own) and by Klöckner & Blöbaum, who has since brought to the literature the Comprehensive Action Determination Model (CADM). The CADM utilizes the abovementioned theories as its basis, combining similar constructs and making further structural modifications to reach the author's desired results. The CADM assumes that individual behavior is rooted in normative processes but is determined by influences from three sources: intentional, situational, and habitual (Klöckner & Blöbaum, 2010). These influential sources (intentional, situational, habitual) are assumed as intents and are determined in the short term whereas norms are general and determined across a lifetime. Once paired with attitudes and perceived behavior control, norms are used to guide general intentions and provide a lens through which choices are viewed and determined. Ultimately, social norms, awareness of needs and consequences, and perceived behavioral control impact the stable personal norm, while social and personal norm impact intention. Perceived behavioral control and situational influences (such as access to resources) impact habitual processes, and finally, intention, habitual processes, perceived behavioral control, and situational influences impact decision-making.

2.5 Political Economy & Structural Factors

An alternative approach to predicting behavior is to take a political-economic approach which investigates behavior not at the individual, but rather structural level (e.g., Alston et al., 2000; Birner & Resnick, 2010; Jarosz, 2011; Krueger, 1996; Olper, 2001; Swinnen, 2010). The integration of structural and political economic variables is nothing new, as Lockertz (1990) details, however, it should be done in conjunction with other attitudinal constructs as advocated by Reimer and colleagues (2012a). This school of analysis is derived from a more discursive form of agricultural economics and is born from tracking the impacts of the farm bill and its effect on the expression of farm typology (Goss et al., 1979). In reviewing the political-economic literature on agriculture, several key factors emerge as crucial considerations in agreement with the “adoption” focused literature (e.g.Prokopy et al., 2019). Leased acres play a significant role, influencing not only the scale of operations but also the dynamics of land use and management decisions (Bray, 1963; Katchova & Ahearn, 2014). Land tenure arrangements, whether through ownership or leasing, directly impact farmers' access to resources and their long-term planning strategies. The number of employees within agricultural enterprises is another vital aspect, affecting productivity levels, labor management practices, and overall economic sustainability (Arcas et al., 2011; Harrison & Getz, 2015). Additionally, the sources of information that farmers rely on, ranging from traditional knowledge to modern technological advisors, shape decision-making processes and capacity for farmer innovation (Chapman et al., 2009; Jalali et al., 2020). Understanding these factors is essential to consider as confounding variables to potentially augment more developed psychological models to capture all the context necessary to make policy prescriptions in instances where the complex interplay between farmer livelihood—the monetary gain from farming—and moral quandary-farmers' beliefs of pro-environmental farming—intersect.

2.6 Research Gap

In this chapter, I have reviewed the climactic threats to agriculture, the potential adaptation of food systems to remain resilient in the face of said threat, and methods of predicting behavior utilized by researchers to predict farm adoption behavior. In particular, I highlight the lack of research conducted on post-intervention explanations for the maintenance of practices adopted during the intervention. Using the various behavioral models outlined in section 2.4, this thesis aims to utilize the CDFA OEFI grants to help identify the best model for the persistence of pro-ecological farming practices.

Chapter

3. METHODOLOGY

This study aims to gain an understanding of the factors affecting the post-funding persistence of BMPs in CDFA OEFI grant recipients (HSP, SWEEP, AMMP, DDRDP) through a survey of farm managers in California who received grant funding (Table 1 for discussion on programs). My methodology aims to identify the best model of behavior (see sections 2.4 and 2.5) that explains the persistence of OEFI-funded cover crops, compost, and soil moisture sensors and then use that model to make general claims about the factors that best predict persistence. To achieve this, I analyze the continuance of practices, the challenges that those adopting practices face, and the impact of various aspects of the grant process using logistic regression.

Table 1. CDFA-OEFI program characteristics and practices evaluated. †included in regression analysis for persistence

Program	**Goals**	**Practices Evaluated**	**Eligibility**
AMMP	Mitigate GHGs, Reduce manure run-off	Solid separation system, Flush to scrape system, Compost bedded pack barn	Dairy and/or livestock operations
DDRDP	Mitigate GHGs, Reduce air pollution, Reduce manure run-of, Produce renewable energy	Digester	Dairy operations
HSP	Mitigate GHGs, Enhance carbon sequestration, Enhance soil health	Cover crop†, Compost†, Hedgerows, Edge-of-field practices	Agricultural operations
SWEEP	Mitigate GHGs, Reduce water use, Reduce energy use	Micro irrigation, Soil moisture sensor†, Solar, Irrigation management subscriptions, Pump, VFD pump, Weather Station	Agricultural operations

3.1 Study Population

The chosen sampling design was a census survey of all CDFA OEFI grant recipients soliciting the primary farm managers for response, totalling 1652 participants of which 1349 were able to be contacted (Table 2, for further discussion, see section 3.1.1 and Table 4). Our sample included beneficiaries of the Healthy Soils Program (HSP) from 2018 to 2020 (n = 591, non-duplicate 484), the State Water Efficiency Enchantment Program (SWEEP) spanning from 2014 to 2019 (n = 829, non-duplicate 650), the Alternative Manure Management Program (AMMP) covering the period from 2017 to 2020 (n = 115, non-duplicate 104), and the Dairy Digester Research and Development Program (DDRDP) operating from 2015 to 2020 (n = 117, non-duplicate 111). This sampling strategy facilitated a comprehensive analysis encompassing diverse practices of varying magnitudes, state-wide perspectives and perceptions, and overarching attitudes prevalent across different farm types such as dairies, orchards, and annual crop farms, among others.

Table 2. Survey response rates.

Program	**N**	**Responses**	**Response %**
HSP	484	194	40%
SWEEP	650	141	22%
AMMP	104	38	37%
DDRDP	111	30	27%
Total	1349	403	30%

Table 3 provides a comprehensive overview of the demographic characteristics observed in the study cohort. The data illustrates that, in comparison to the statewide averages in California, recipients of OEFI grants predominantly operate larger-scale farms with reduced leased land holdings. These farms exhibit a higher employee count and a greater representation of male managerial personnel, consistent with the age distribution typically observed among farm managers statewide. Furthermore, the study cohort encompasses a reduced extent of irrigated land and less coverage within Sustainable Groundwater Management Act (SGMA) sub-basins. Notably, a significant proportion of these farms demonstrate organic certification or engage with non-traditional suppliers, reflecting distinctive operational paradigms within this subset of agricultural enterprises.

Table 3. Mean values of farm and farm manager respondent characteristics for total sample and by program.

± Responses to "What percentage of the croplands you manage are irrigated?"

Variable	**HSP (n)**	**SWEEP (n)**	**AMMP (n)**	**DDRDP (n)**	**OEFI (N)**	**California**
Average Operation Acres	995 (133)	2428 (100)	1367 (26)	1724 (19)	1595 (278)	351
Leased Acres/ Operation Acres (%)	25% (133)	13% (96)	NA (0)	NA (0)	23% (229)	45%
Employees	5 (136)	36 (100)	21 (3)	35 (19)	20 (285)	2
Male (%)	70% (133)	82% (100)	93% (29)	100% (19)	79% (281)	64%
Age	56 (136)	53 (96)	50 (28)	54 (18)	54 (278)	58
Years in Agriculture	27 (141)	29 (105)	34 (29)	36 (19)	29 (294)	NA
Irrigation (%) ±	86% (128)	96% (106)	92% (27)	96% (18)	91% (279)	98%
SGMA (%)	14% (140)	51% (106)	7% (30)	83% (18)	31% (294)	88%
Socially Disadvantaged (%)	13% (193)	20% (140)	0% (38)	6% (28)	18% (399)	19%
Four Year Degree (%)	88% (193)	90% (144)	58% (38)	57% (28)	84% (403)	NA
Organic (%)	28% (144)	11% (104)	40% (30)	0% (18)	22% (296)	4%
Non-traditional Market (%)	40% (143)	22% (103)	58% (38)	68% (28)	39% (312)	12%
Insecure Contract (%)	66% (123)	45% (93)	40% (30)	37% (24)	53% (270)	NA

3.1.1 Contact Information

Through collaboration with the CDFA, master data sheets from the OEFI were obtained for the grants in the abovementioned section which included some combination of names, company names, mailing addresses, email addresses, and assessor parcel numbers (APN) for the land on which the grant practices were implemented. The AMMP data request contained all necessary contact information, the HSP data request was missing mailing addresses, the DDRDP request was missing email addresses though had them for the developers of the dairy digesters, and the SWEEP request had different levels of information. SWEEP round two contained all information, round three was missing mailing addresses, rounds four through seven had nearest cross streets or mailing addresses, and rounds eight and nine had all relevant information.

3.1.2 Acquiring Unknown Mailing Addresses

In a bid to acquire unknown mailing addresses, I matched APNs to mailing addresses via a web scraping program coded using Python v3.11.1 (Rossum, 1995) and libraries BeautifulSoup v4.11.2 (Richardson, 2007), NumPy (Harris et al., 2020), OpenCV v4.7.0.68 (Bradski, 2000), Pandas v1.5.3 (McKinney & others, 2010), Scikit-Learn v1.2.1 (Pedregosa et al., 2011), and Selenium v4.8.0. APN data was first cleaned by removing text from the column reporting APNs and then ensuring that they were delineated by commas if there were multiple APNs. Next, the data was passed into Python where web scraping was implemented.

3.1.2.1 Web Scraping

The first round of web scraping was conducted on the California Strategic Growth Council's RePlan tool (CSGC, n.d.). Using Selenium's web driver, county and APN(s) were passed into the tool's input boxes, if the tool found the land parcel, a screen grab of the website was collected and if an address was associated with the APN the mailing address was collected using BeautifulSoup. Grants with located addresses were stored in a "success" data frame and grants that failed were passed on to the next round of scraping. Grants with multiple addresses associated with the various parcels first were referenced to the cross streets that some data requests contained, if one address matched a cross street it was passed to the "success" data frame, and all others were subjected to a predetermined voting methodology.

Round one of the voting methodologies involved searching for the address with the highest occurrence rate for queries related to the grant, if an address satisfied this requirement it was passed to the “success” data frame. If all addresses were found in equal numbers, OpenCV was employed to search for squares of grey pixels in the screen grabs of the parcel maps (which indicated the presence of a building). If only one of the parcels contained what was determined to be a building, that address was passed on to the “success” data frame. Finally, a tiebreaker was employed by using Harris Corner Detection and Houghline Transform to try and determine which parcels touched the most other parcels associated with the query and winners of the tiebreaker were passed to the “success” data frame, if no mailing address could be determined as the best, the top addresses were passed into a “check” data frame to manually be chosen. Following this round, 63% of addresses were identified.

The second web scraping used the same methodology as the first round but was used to scrape the ReportAll Online tool (Real Estate Portal USA, n.d.). Parcel numbers were passed through the tools input boxes and if parcels were identified, the mailing address and the owner’s mailing address were stored. If the tool identified a mailing address of the physical location, the aforementioned voting methodology was used to determine the utilized mailing address. If the tool was unable to find the physical mailing address of the parcels, my code checked if the owner's name of any of the found parcels matched the first name, last name, or company name of the grant applicant and stored the owner's mailing address in the "success" data frame. If multiple addresses were associated with the owners (i.e. one was attributed to the grant applicant and one to the company) then the company address was stored in the "success" data frame. If no addresses were determined in this round, the data was passed on to the third round of scraping. Following this round, 84% of addresses were identified.

The third round of web scraping the APN data was manipulated to add all permutations of between one and two zeros to the front of the parcel number and between one and four zeros to the end of the parcel number and passed them through the ReportAll Online tool. This tactic was employed as during the testing of the scraping program it was found that at times the ReportAll Online tool was not resilient to implied leading or trailing zeros (whereas RePlan was). During the initial clean, it was found that some applicants would forgo entering these zeros, only entering the non-zero parts of the APN—prepending and appending zeros were used to attempt to correct this error. Due to the manipulation of data in this stage, mailing addresses were only added to the “success” data frame if one of the cross streets listed as part of the application matched the address in the tool or if the name of the applicant or business matched the owner information listed in the tool. All grants that failed to have mailing addresses identified were passed on to the final round of web scraping. Following this round 86% of addresses were identified.

The final round of web scraping utilized the “success” data frame to match APNs structure to the unidentified land parcels. Using the “success” data frame, APNs were decomposed into binary features which indicated which number was in which position in the APN, the final APNs then were assigned permutations of missing values in between its numbers until its array length was as long as the longest found in the “success” data frame to tease out “fuzzy” APNs. Using Scikit-Learn a k-nearest neighbors imputation algorithm was used for each permutation of the APN (i.e. only one manipulated APN was exposed to the training “success” data at a time)and the APNs were re-passed through the scraping methodology from round two with the control for cross streets and owner names in round three. When this round was concluded, 87% of addresses were identified. All other grants were manually looked up in Google to try and find mailing addresses for the farm names. In total 92% (1519) of grants with missing mailing addresses were successfully ascertained. Finally, within programs (e.g., SWEEP was checked with SWEEP only, not HSP) addresses were searched for duplicates, and duplicates were removed from mailing lists (total duplicates and canceled project: 303).

Table 4. True study population after duplicate checking

Program	**N**	**Minus Duplicates**	**% Non-Duplicate**
HSP	591	484	81.9%
SWEEP	829	650	78.4%
AMMP	115	104	90.4%
DDRDP	117	111	94.9%
Total	1652	1349	81.7%

3.2 Survey Design

Data collection was conducted utilizing Qualtrics online surveys for each grant program of study interest. This section describes the survey design process, data collection process, and archiving process.

While content differed across grant program surveys, the content of each was composed of seven main sections: general questions on the farmers' grant (what practices were funded, years, did technical assistance providers aid in the grant, etc.), practice-specific questions (experiences with the practice, benefits realized, etc.), theory questions (Table 5), biodiversity and systems thinking (what aspects they manage for, how much they view their farm as a system, etc.), application and administrative processes (how easy working with the CDFA was), and demographic questions (Table 6). The HSP survey can be found in Appendix A. In total, the surveys ranged from 72 to 119 questions and were estimated to take between 20-30 minutes to complete.

The survey design process was guided by Dillman et al. (2014), Fishbein & Ajzen (2015), Hankins et al. (2000), Harwood et al. (1999), and Klöckner (2013). For practices with sufficient recipients to conduct my analysis, the practice-specific portion of the survey included theory-based questions measuring the RAA and CADM. Reasoned action approach questions for the theoretical constructs (see 2.4) were constructed following Ajzen (2019)'s Constructing a Theory of Planned Behavior Questionnaire with further questions adapted from Fishbein & Ajzen (2015)'s appendix for sample measures of the TPB constructs. Comprehensive Action Determination Model questions were adapted from Klöckner (2013) and Klöckner & Blöbaum (2010). The remainder of the questions were created to measure the CDFA's parameters of interest using qualitative data obtained from prior interviews.

Table 5. Sample Construct Questions

Construct	Question
RAA Attitudes	Please fill in the blank: My using cover crops in the next 12 months would be________. *Very unenjoyable to Very enjoyable*
RAA PBC	My decision to use cover crops in the next 12 months is completely up to me. *Strongly disagree to Strongly Agree*
RAA AVC	I have the knowledge and technical skills to successfully cover crop over the next 12 months. *Strongly disagree to Strongly Agree*
RAA Norms	Most farmers I respect and admire will use cover crops in the next 12 months. *Strongly disagree to Strongly Agree*
CADM Awareness of Consequence	Planting cover crops protects my farm’s soil. *Strongly disagree to Strongly Agree*
CADM Awareness of Need	Leaving soil bare and without cover crops hinders the optimal operation of my farm. *Strongly disagree to Strongly Agree*
CADM Habits	Cover crops no longer require much thought to implement and manage. *Strongly disagree to Strongly Agree*

Question types on the survey included Likert scales, multiple choice, demographic, and text entry. Display logic was used to ensure that questions relevant only to certain respondents were only shown to said respondents. Display logic allowed for a proper flow of questions, such as only showing the compost block to respondents whose grant included compost or showing questions on the efficacy of technical assistance providers (TAP) only to respondents who were aided in their grant execution by TAPs. Finally, response forcing and validation were used to ensure clean data (i.e. only allowing numerical entry for birth year) and to ensure that crucial survey points were not skipped (informed consent, which practices were included in their grant, persistence intentions, etc.). Trusted farmers, research collaborators, and non-governmental organization employees trial-tested the survey and provided feedback prior to distribution.

Table 6. Sample HSP Questions

Type	Question
General	Were you awarded more than one Healthy Soils Program (HSP) grant between 2018-2020?
Practice	How many years of experience did you have with compost prior to your HSP project?
Benefits	The following farming conditions are often impacted by composting. Please rate what type of an impact you have seen from compost application on your farm. *Soil Structure*
Biodiversity	Please indicate your level of agreement or disagreement with the following statements about farm systems management. *When I make decisions on my farm, I tend to see all kinds of possible consequences for each decision.*
Admin	Did changing your CDFA contact person negatively impact your experience with the HSP?
Demographic	What is your gender identity?

3.2.1 Distribution

Survey distribution utilized personalized and repeated contact through different communication mediums to reduce non-response bias (Dillman et al., 2014; Monroe & Adams, 2012). Using the provided and acquired mailing addresses, participants were mailed a solicitation letter containing survey information and a QR code directing them to the survey printed on Cal Poly NRES stationary with a CDFA logo. White envelopes were hand-addressed using green ink to reduce the effects of non-response bias. White envelopes with green ink are associated with higher response rates (Taylor et al., 2006) and hand addressing similarly has been shown to increase response rates (Scott & Edwards, 2006). Additionally, a $2 gift was included to boost the response rate; two $1 bills were used as they were more widely available and have been shown to have the same efficacy as a $2 bill (Lesser et al., 2001). One week after the initial mailing, a reminder email was sent out to recipients. Two weeks after the initial mailing another reminder email was sent out, and four weeks after reminder texts were sent. NGO partners were also asked to reach out to participants during this time frame to solicit their participation. Early exit bias checks were conducted periodically by researchers during the survey collection period to ensure that certain questions were not causing participants to not complete the survey. Participants were additionally given a $20 visa gift card upon completion of the survey.

3.2.2 Data Archiving

Data was obtained from Qualtrics by downloading response data in xlsx format with all fields and numeric values selected as output. Data was stored in two locations and when data was manipulated, each new data frame was stored separately from the original so as not to alter the original data. Most data were pre-cleaned in Qualtrics to reduce potential errors using the recode and question export tag functions. Questions were generalized into 4 question types (general, practice, theory, and biodiversity/systems thinking) and assigned code syntax. Each question was given a survey prefix which denoted the program, a practice code which denoted which practice the question was asking about (if applicable), a theory code (if applicable; to denote which theory it was testing), a constructing code (if applicable; to denote which construct of a theory was being tested), a matrix code (if applicable; to denote the matrix in which it was found, replaces theory and construct code when in a matrix), a number (if attached to a construct), text (if applicable;

denotes what the question is asking about), and a broadcast operator to denote display logic where applicable (Appendix B). Output data was standardized such that Likert questions had 1 always as 'negative' and 5 as 'positive' except for some exceptions (see Appendix B). Descriptive questions were always numbered for the order in which options appeared in the survey, unsure was standardized to output as -1, and binary was standardized to yes as 1 and no as 0.

3.2.3 Data Cleaning

Data cleaning involved downloading data from Qualtrics, with subsequent observations revealing instances of incomplete data. Specifically, where multiple questions implied answers to others, I employed interpolation of missing values. For instance, if total operational acreage and total leased acreage were known but total owned acreage was not, the latter was inferred as the difference between total operational and total leased acreage. Additional columns were introduced in the Excel sheets to explore supplementary research inquiries, such as identifying individuals with stacked grants or creating ratios relating to owned versus total acreage.

Furthermore, to facilitate deeper analysis, dedicated spreadsheets were created, each focusing exclusively on grants of a specific type, such as cover crops. To ensure compatibility with analytical tools like Julia, missing data points were standardized by assigning them a value of -99. Subsequently, the entire dataset underwent a conversion from the 'Any' data type to 'Float64,' with -99 values being reclassified as 'missing' to facilitate accurate filtering during logistic regression analyses. Detailed information regarding the coding procedures can be found in Technical Appendix A.

3.3 Data analysis

After data collection the number of practice responses were tallied and it was determined that proper analysis could only be conducted on cover crops, compost, and soil moisture sensor. Data analysis was conducted in Julia v1.8.5 (Bezanson et al., 2017) using GLM 1.8.1, CSV 0.10.7, DataFrames 1.3.6, FixedEffectModels 1.7.0, Missings 1.0.2, Plots 1.35.8, PlotThemes 3.1.0, PyCall 1.94.1, StatsBase 0.33.21, StatsModels 0.6.33, XLSX 0.8.4,, StructuralEquationModels 0.1.0, GLMNet 0.7.1, CategoricalArrays 0.10.7, and MLJ 0.18.6. Data was read into Julia after the initial cleaning. To create models of behavioral constructs, latent variables of the constructs in the three models, RAA, CADM, and CADM + Political

Economy Variables were created (see Table 8) using the following equation (Cronbach, 1951):

$$\alpha = (\frac{k}{k-1})(1 - \frac{\sum_{i=1}^{k}\sigma_{y_i}^2}{\sigma_x^2})$$

Following the creation and validation of latents, logistic regression models as specified in section 4.1 were created following the below estimation equation:

$$\mathbb{P}(y_i = 1 \mid x_1, \dots, x_n) = \frac{e^{\alpha + \beta_1 x_{1+\dots+}\beta_n x_n}}{1 + e^{\alpha + \beta_1 x_{1+\dots+}\beta_n x_n}}$$

In determining the structural variables for inclusion, we referred to relevant literature sources (Alston et al., 2000; Birner & Resnick, 2010; Bray, 1963; Chapman et al., 2009; Goss et al., 1979; Jarosz, 2011; Krueger, 1996; Swinnen, 2010) to identify constructs that align with variables in our dataset. Given the potential for multicollinearity due to highly correlated data points, such as multiple acreage measurements in our survey, we employed Bayesian regression with a Gaussian prior, as outlined below, to guide the selection of features for the political-economic model:

$$\widehat{\boldsymbol{\beta}}_{\boldsymbol{MAP}} = \operatorname*{\mathbf{argmax}}_{\boldsymbol{\beta}} \mathbb{P}(\boldsymbol{\beta} \mid \boldsymbol{y})$$

Writing out the posterior distribution using Bayes theorem, ignoring the denominator (as we are maximizing over β), and taking the log yields:

$$\underset{\boldsymbol{\beta}}{\mathbf{argmax}}(\mathbf{log}[\mathbb{P}(\,\boldsymbol{y}\mid\boldsymbol{\beta})] + \mathbf{log}[\mathbb{P}(\boldsymbol{\beta})])$$

Where β is a vector of predictors and y is a vector of outcome variables. Assuming $y_i \sim N(\beta^T x_i, \sigma^2)$ we arrive at the analytical solution found in equation 2:

$$\mathbb{P}(y\mid\beta) = \prod_{i=1}^{N} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(y_i - \beta^T x_i)^2}{2\sigma^2}}$$

Taking the natural log of both sides we arrive at:

$$\mathbf{log}[\mathbb{P}(\,y\mid\beta)] = \sum_{i=1}^{N} [\mathbf{log}\frac{1}{\sigma\sqrt{2\pi}} - \frac{1}{2\sigma^2}\,(y_i - \beta^T x_i)^2]$$

Assuming a Gaussian prior distribution function $\beta_i \sim N(0,\,\tau^2)\ \forall_i = 1,\ldots,n$ we arrive at the equation to estimate:

$$\underset{\beta}{\mathbf{argmin}}[\,\|y - x\beta\|_2^2 + \frac{\sigma^2}{\tau^2}\,\|\beta\|_2^2] => \underset{\beta}{\mathbf{argmin}}[\,\|y - x\beta\|_2^2 + \lambda\|\beta\|_2^2]$$

Finally, features heavily weighted by the regression were incorporated into the model.

Chapter

4. ANALYSIS

Understanding the factors that influence the persistence of funded farm practices is crucial for promoting sustainable agricultural systems. In this study, I employ a blend of theoretical frameworks including the Reasoned Action Approach (RAA), Comprehensive Action Determination (CADM), and CADM augmented with political economic factors to comprehensively assess the determinants of behavior change in the long-term adoption of funded farm practices. The RAA, deeply rooted in social psychology and extensively discussed by Fishbein and Ajzen (2015), focuses on the influence of beliefs, attitudes, and subjective norms on behavior. Conversely, Comprehensive Action Determination, as elucidated by Klöckner (2013), expands this framework by considering additional factors such as resources, opportunities, and constraints that play a significant role in shaping behavior. For further discussion on the various choice models in psychology see section 2.4. By comparing and modifying CADM with political-economic factors (section 2.5), this study aims to not only gain an understanding of the best model for continuing agricultural persistence research but also to bridge the gap between theoretical frameworks and practical applications in promoting sustainable agricultural practices. This analysis is particularly poignant as it provides a nuanced understanding of the interplay between psychological, social, and economic factors in driving and sustaining agricultural practices over time.

The choice of logistic regression as the analytical framework for comparing the RAA, CADM, and CADM with political economic factors is grounded in several methodological considerations that align with the nature of behavior change research and the specific objectives of this study. Firstly, logistic regression is particularly well-suited for modeling binary or categorical outcomes, which are commonly encountered in behavior change studies (see Prokopy et al., 2019; Rudnick et al., 2021; Ulrich-Schad et al., 2017). In my context, the outcome of interest involves binary categorization (persist, revert).

Logistic regression enables me to model and interpret the probability of such binary outcomes as a function of predictor variables, which is essential for assessing the effectiveness of the RAA, CADM, and modified CADM in predicting behavior change. Secondly, logistic regression accommodates a mix of predictor variables, including both continuous and categorical variables (Peng et al., 2001). This flexibility allows me to incorporate a wide range of factors implicated in behavior change, such as beliefs, attitudes, resources, and political-economic considerations. Finally, logistic regression facilitates model comparison through statistical criteria such as likelihood ratio tests, Akaike Information Criterion (AIC), and deviance. These criteria enable us to quantitatively assess the fit and performance of the RAA, CADM, and CADM with political economic factors models, thereby identifying the model or combination of models that best explain the observed behavior change patterns in funded farm practices.

4.1 Model Creation

My model selection process commenced with an exhaustive review of the extant literature pertaining to the utilization of the RAA and CADM within the domain of behavior change research specific to funded farm practices (chapter 2). Due to constraints in the number of grants awarded to each incentive program, the statistical analysis was only performed on cover crops, compost, and soil moisture sensor grants. The decision to model by incentive program rather than the overarching program was made to tease out if certain models would better describe different farming practices (e.g., RAA works well for compost but not soil moisture). As described in section 3.2 survey questions (Table 5, Appendix A) pertinent to model creation were adapted from standard RAA questions, CADM meta-analyses, and factors common in political-economic and general adoption literature to create a linked behavioral and structural model(Reimer et al., 2012a). This literature synthesis served as the foundation for the development of survey questions and thus of the latent variables corresponding to each construct encapsulated within the aforementioned theoretical frameworks, encompassing dimensions such as beliefs, attitudes, subjective norms, resources, opportunities, constraints, and political-economic factors. The below figures detail the latent construction used for the models.

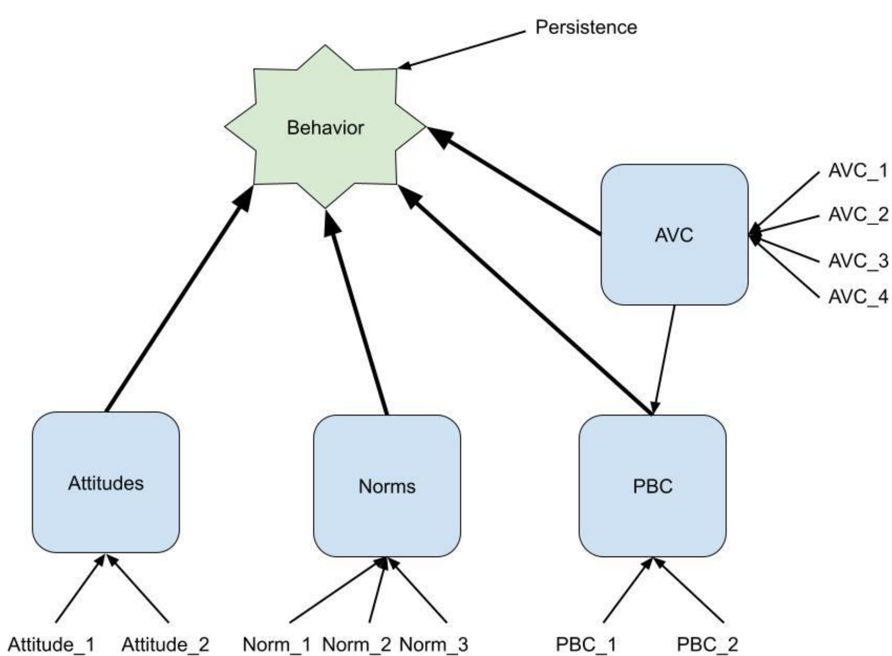

Figure 1. RAA Model Creation

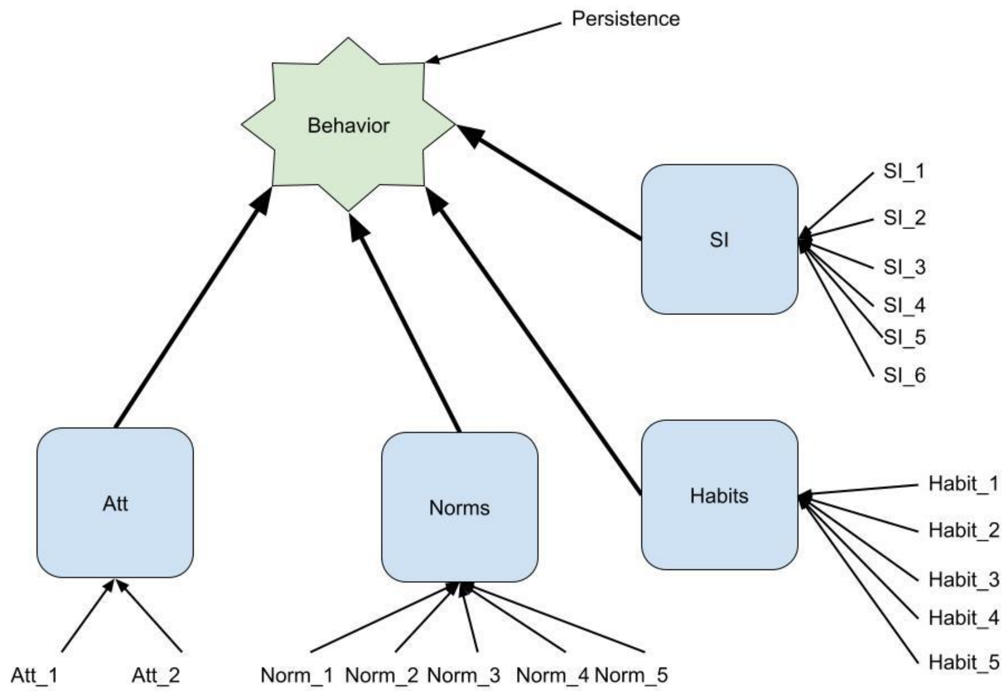

Figure 2. CADM Model Creation

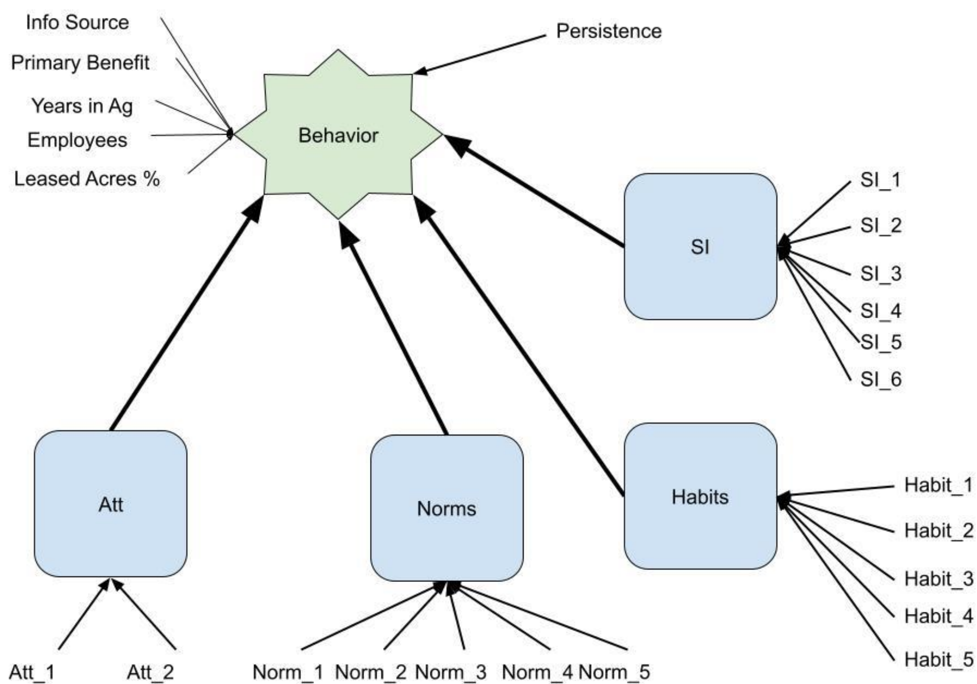

Figure 3. CADM + PE Model Creation

4.1.1 Latent Variables

The complex factors influencing grant recipients (herein, farmers) behavior in California encompass a wide array of economic, social, environmental, and policy-related aspects. These factors can include varying farm sizes and types, diverse production systems, fluctuating market demands, evolving regulatory frameworks, and dynamic socio-cultural contexts (section 2.5). Additionally, farmers' decision-making processes are influenced by personal beliefs, risk perceptions, financial constraints, access to resources, technological innovations, and local community dynamics. This intricate web of influences creates a challenging environment for measuring farmer behavior using traditional scales or questionnaires; employing latent variable modeling techniques can help capture the underlying complexity and interrelationships among these factors, offering a more comprehensive understanding of farmer behavior despite the challenges posed by low Cronbach's alpha values.

Using Julia, latent variables were created based on variables found in Table 7 the constructs detailed in Figures 1-3 utilizing the estimation equation in section 3.3 (Bezanson et al., 2017; Cronbach, 1951).

Table 7. Cover crop questions used for latent variable creation. †Included in CADM but not RAA

Code	Question
Att_1	Please fill in the blank: My using cover crops in the next 12 months would be________. ***Very unenjoyable to Very enjoyable***
Att_2	Please fill in the blank: My using cover crops in the next 12 months would be________. ***Very harmful to Very beneficial***
Norm_1	Most people whose opinions I value would approve of me using cover crops in the next 12 months. ***Strongly Disagree to Strongly Agree***
Norm_2	Most farmers like me will use cover crops in the next 12 months. ***Strongly Disagree to Strongly Agree***
Norm_3	Most farmers I respect and admire will use cover crops in the next 12 months. ***Strongly Disagree to Strongly Agree***
Norm_4†	Leaving soil bare and without cover crops hinders the optimal operation of my farm. ***Strongly Disagree to Strongly Agree***
Norm_5†	Planting cover crops protects my farm's soil. ***Strongly Disagree to Strongly Agree***
AVC/SI_1	I have the knowledge and technical skills to successfully cover crop over the next 12 months. ***Strongly Disagree to Strongly Agree***
AVC/SI_2	I have the labor and equipment resources to successfully cover crops over the next 12 months. ***Strongly Disagree to Strongly Agree***
AVC/SI_3	Environmental factors (water availability, rainfall timing, temperatures, etc.) will impact my decision to use cover crops over the next 12 months. ***Strongly Disagree to Strongly Agree***
AVC/SI_4	Cover crops pay for themselves and are worth doing even in the absence of incentives. ***Strongly Disagree to Strongly Agree***
PBC_1/SI_5	How much control do you have over your use of cover crops in the next 12 months. ***None at all to A great Deal***
PBC_2/SI_6	My decision to use cover crops in the next 12 months is completely up to me. ***Strongly Disagree to Strongly Agree***
Hab_1†	It would be difficult to manage my farm without cover crops. ***Strongly Disagree to Strongly Agree***
Hab_2†	Cover crops are now part of my farm management routine. ***Strongly Disagree to Strongly Agree***
Hab_3†	Cover crops no longer require much thought to implement and manage ***Strongly Disagree to Strongly Agree***
Hab_4†	I like the way that cover crops make my fields look. ***Strongly Disagree to Strongly Agree***
Hab_5†	Please fill in the blank: For me to use cover crops in the next 12 months will be_______. ***Extremely difficult to Extremely easy***

Cronbach's alpha is a measure of internal consistency reliability commonly used in research to assess the reliability of a scale or a set of items intended to measure a construct; it quantifies the extent to which the items in the scale are correlated with each other, indicating the degree to which they are consistently measuring the same underlying concept.Cronbach's alpha is often reported when researchers utilize scales or questionnaires to measure variables such as attitudes, beliefs, or behaviors. A high Cronbach's alpha value (typically above 0.7) suggests that the items in the scale are highly correlated and are likely measuring the intended construct reliably.

Using latent variables with a Cronbach's alpha in the range of 0.4 to 0.6 can be justified in certain research contexts (Bernardi, 1994). While a Cronbach's alpha below the conventional threshold of 0.7 may indicate lower internal consistency among the items in a scale, it does not necessarily render the scale unusable or devoid of value; in cases where the construct being measured is complex or multidimensional—such as attitudes toward a multifaceted issue (environment) or a combination of cognitive and affective components (performance of behavior)—a lower Cronbach's alpha may be expected due to the inherent diversity of items (differing aspects of norms and external influences having differential influences on the scale by individual). Table 8 details Cronbach's alpha for my model specification, notably, more complex items such as situational influences and aspects of control tend to have lower Cronbach's alpha.

Table 8. Cronbach's alpha by model and practice

	Cronbach's Alpha for All Models		
	Cover Crops	Compost	Soil Moisture
RAA			
Norm	0.8227	0.8687	0.7291
PBC	0.5274	0.4671	0.6741
AVC	0.5714	0.392	0.5969
Attitudes	0.6136	0.5949	0.5365
CADM			
Norm	0.8161	0.797	0.794
Habits	0.7647	0.8216	0.6348
Attitudes	0.6034	0.5949	0.5685
Situation	0.4754	0.5242	0.7193
CADM +			
Norm	0.7829	0.7904	0.8149
Habits	0.7579	0.8143	0.6417
Attitudes	0.608	0.6166	0.5624
Situation	0.339	0.5204	0.7325

4.2 Modelling

Following the creation of latent variables, logistic regression models were fitted utilizing the constructed latent variables as predictor variables (see section 3.3). Logistic regression analysis was used to predict the binary outcome of behavior change—defined by the continued adoption or non-adoption of funded farm practices—based on the explanatory capacity of selected models of interest (RAA, CADM, and CADM with political economic factors). Models were fit by specifying a data frame of predictors necessary for the model, dropping all observations with missing data, creating the latent variables, and then running the regression (Technical Appendix B). The output for each grant type analyzed and model used are found below in Table 9.

Table 9. Logistic regression output

	Cover Crops			Compost			Soil Moisture Sensor		
	RAA	CADM	CADM + PE	RAA	CADM	CADM + PE	RAA	CADM	CADM + PE
(Int.)	-5.131**	-4.790*	9.100	-3.457**	-4.177**	-2.877	-1.620	-0.614	-1.716
	(2.487)	(2.726)	(8.074)	(1.690)	(1.667)	(2.280)	(1.755)	(1.777)	(2.231)
RAA_A	0.751***			0.339**			0.435**		
	(0.215)			(0.146)			(0.199)		
RAA_PBC	0.065			-0.108			0.068		
	(0.179)			(0.163)			(0.142)		
RAA_AVC	-0.078			0.189**			-0.063		
	(0.108)			(0.095)			(0.096)		
RAA_N	0.085	0.066	-0.344	-0.002	-0.057	-0.021	-0.045	-0.047	-0.034
	(0.121)	(0.095)	(0.238)	(0.085)	(0.070)	(0.082)	(0.119)	(0.092)	(0.106)
CADM_HP		0.155	0.474**		0.153**	0.087		0.440***	0.461***
		(0.105)	(0.210)		(0.070)	(0.085)		(0.145)	(0.168)
CADM_A		0.576**	1.150**		0.286*	0.132		0.176	0.121
		(0.224)	(0.569)		(0.169)	(0.196)		(0.225)	(0.262)
CADM_SI		-0.102	-0.507*		0.062	0.074		-0.150*	-0.144*
		(0.097)	(0.277)		(0.072)	(0.096)		(0.078)	(0.087)
Info Farm			-0.941*			-0.295			0.303
			(0.492)			(0.215)			(0.337)
Yrs Ag.			-0.072**			0.006			0.004
			(0.033)			(0.022)			(0.019)
Practice Benefit			-0.120			0.234			-0.052
			(0.795)			(0.415)			(0.476)
# of Empl.			0.063			0.061			0.001
			(0.067)			(0.057)			(0.002)
Leased Acres %			-0.222			-0.335			0.805
			(1.497)			(0.766)			(1.061)
N	76	73	53	105	105	77	98	94	77
AIC	78.35	72.8	48.36	115.5	112.53	88.17	121.32	106.65	97.84
Dev.	68.35	62.8	28.36	105.5	102.53	68.17	111.32	96.65	77.84
McFadden R^2	0.25	0.28	0.54	0.13	0.16	0.18	0.05	0.14	0.16

p >=* .1; ** .05; *** .01

4.3 Model Performance

The primary criterion for model comparison for evaluating the efficacy and performance of these logistic regression models was the Akaike Information Criterion (AIC). The AIC, renowned for its capacity to balance psychological models' goodness of fit with parsimony, facilitated the identification of optimal models among the competing theoretical frameworks by factoring in both explanatory power and model complexity (Vrieze, 2012). AIC was calculated with the below equation where k is the number of parameters and $\hat{L}$ is maximized value of the likelihood function for the model (Akaike, 1973):

$$AIC = 2k - 2\ln(\hat{L})$$

The comparative examination of Akaike Information Criterion (AIC) values across logistic regression models enabled me to discern models striking an optimal balance between explanatory robustness and model simplicity. Notably, AIC values were consistently lower in the CADM + PE models (refer to Table 9), indicating their superiority despite increased parameters—which may potentially lead to overfitting—and lower sample size (N, Table 9) due to incomplete survey responses. Decreasing sample size typically increases AIC in models due to reduced information, resulting in less precise parameter estimates and decreased model fit; this reduction in information contributes to increased uncertainty in estimating the true relationships between predictor variables and the outcome, leading to greater variability in predictions and reduced reliability (Bozdogan, 1987). Additionally, the model’s additional parameters should—assuming similar levels of model fit lead—to higher AIC, penalizing models with excessive complexity. My results, however, show reduced AIC, mitigating this risk of overfitted models; the additional information provided by the added covariates are positively contributing to model fit. Hence, my analysis unequivocally supports the conclusion that the CADM + PE model excels in predicting persistence.

Additionally, the lower deviance observed in the CADM + PE models within our study serves as a compelling indicator of its superiority. Deviance—a measure of model fit common in logistic regression—reflects the discrepancy between observed and predicted outcomes, with lower values indicating a better fit. The consistently lower deviance in the CADM + PE models, as compared to alternative models, suggests that these models more accurately capture the relationships between predictor variables and persistence. This superior fit implies that the CADM + PE models provide a more precise and reliable estimation of persistence, contributing to their perceived superiority in predictive performance within our research framework.

Finally, the higher McFadden's Pseudo-R2 observed in the CADM + PE models signifies its superior predictive power compared to alternative models. McFadden's R2 is a widely accepted measure of model fit in logistic regression, known for its reliability and interpretability (Veall & Zimmermann, 1994). Unlike traditional R2 measures used in linear regression, McFadden's Pseudo-R2 is specifically designed for generalized linear models, taking into account the likelihood function and model complexity, makes McFadden's Pseudo-R2 a robust statistic for assessing the proportion of variance explained by the model in binary outcome scenarios, such as predicting persistence. The elevated McFadden's R2 values in the CADM + PE models indicate that these models capture a larger portion of the variability in the outcome variable related to persistence. The reliability of McFadden's R2 as a model performance statistic stems from its ability to account for both the goodness of fit and the complexity of the model, striking a balance between explanatory power and model economy. Overall, our stated model performance metrics points towards CADM + PE as the most efficacious theoretical framework or amalgamation thereof for elucidating behavior persistence dynamics in funded farm practices.

Chapter

5. DISCUSSION & CONCLUSION

In this section, I discuss the differences observed between models, explore the distinct dynamics of adoption versus persistence in agricultural behavior change, and examine the influence of individual variables on behavior persistence within the tested frameworks. While my research findings reveal a higher level of persistence (Table 10) than anticipated when compared to the only other study that measured actual persistence, conducted by Jackson-Smith and colleagues (2010), my analysis not only uncovers the unique contributions of CADM, Reasoned Action Approach, and other model adjusters but also illuminates the divergent pathways that shape short-term adoption versus long-term persistence of sustainable agricultural practices. Additionally, I explore the multifaceted nature of individual variables within CADM, such as attitudes, perceived behavioral control, and social influences, to discern their varying impacts on behavior persistence. Furthermore, I discuss how my findings align with existing literature on adoption and persistence, drawing parallels and distinctions to elucidate the unique challenges and opportunities inherent in fostering long-term behavior change in agricultural contexts. Through this exploration, I aim to contribute valuable insights that inform future research directions and practical interventions aimed at promoting agricultural sustainability and resilience.

Table 10. Persistence and abandonment rates (%) of OEFI-funded practices. Practice persistence is defined by an affirmative response to the survey question "Do you intend to use this practice in the next 12 months?"

Practice	**Persistence**	**Abandonment**
HSP Practices (n=437)	71%	29%
SWEEP Practices (n=463)	75%	25%
AMMP Practices (n=45)	93%	7%
DDRDP Practice (n=22)	100%	0%
All OEFI Practices (n=967)	75%	25%
SDFR Respondents (n=51)	82%	18%
Non-SDFR (n=283)	72%	28%

5.1 Models

In my analysis, I examined three models: the Reasoned Action Approach (RAA), Comprehensive Action Determination Model (CADM), and CADM with Political Economic factors (CADM + PE). Among these models, the highest performance—ones that explained persistence best—was observed in CADM + PE, followed by CADM, and finally RAA (Table 9). The superiority of the Comprehensive Action Determination Model over the Reasoned Action Approach is evident due to several inherent advantages in understanding the persistence of post-grant behavior (Klöckner, 2013). CADM's holistic perspective enabled a thorough evaluation of the various factors influencing practice persistence within agricultural settings by encompassing not just individual beliefs and attitudes—as is the case in RAA—but also societal implications and performance-based processes, offering a more nuanced comprehension of the multifaceted dynamics shaping behavior change (Klöckner, 2013).

One of CADM's key advantages is its ability to identify actionable determinants directly impacting behavior. This primarily was through the pathway of habitual processes, followed by social needs and consequences, and institutional facilitation, all of which played crucial roles in farmers' decisions regarding the continuation of grant-funded practices (Babin et al., 2024). In contrast, the Reasoned Action Approach's narrower focus on individual-level beliefs and intentions may have overlooked these broader contextual influences, thereby limiting its explanatory power in predicting long-term behavior persistence (Frey & Rogers, 2014). My research findings align with Klöckner's (2013) meta-analysis, which positions the CADM as the most effective general model of environmental behavior. CADM has proven to be a robust framework for understanding behavior change in various contexts (Klöckner, 2013). However, its applicability to more complex decision-making scenarios, such as those in farming, may encounter limitations due to the absence of certain political-economic variables (Dayer et al., 2018). In agricultural settings, decisions are heavily influenced by factors such as government policies (e.g., the farm bill), access to crop insurance, and the overall economic viability of farming operations (Krueger, 1995). These factors—leased acre ratio, employees, years in agriculture, etc.—can significantly impact farmers' risk tolerance and decision-making processes, making their choices more nuanced and intricately linked to their economic sustainability (Falco et al., 2014).

My analysis underscores the importance of blending CADM with context dependent influences—political economic variables—noted above—by revealing notable improvements in model performance when political economic variables are incorporated into CADM. Specifically, variables such as leased acreage percentage of the farm, sources of information accessed by farmers, the number of employees on the farm, years of experience in agriculture, and farmers' perception of the primary benefits of adopting certain practices on their farms were found to significantly enhance the model's predictive accuracy (Table 9).

The inclusion of these political economic variables in CADM not only bridges the gap between theory and practice but also acknowledges the multifaceted nature of decision-making in agricultural contexts. CADM + PE sheds light on the complex interplay between regulatory frameworks, economic incentives, and individual motivations, all of which influence farmers' behaviors and choices regarding sustainable agricultural practices (Arbuckle et al., 2015; Falco et al., 2014; Medellín-Azuara et al., 2011). The findings of this study, indicating that the Comprehensive Action Determination Model with Political Economic factors (CADM + PE) outperforms other models in predicting persistence in sustainable agricultural practices, align with Dayer et al. (2018)'s framework regarding factors that facilitate persistence. Dayer suggests that persistence is more likely to occur when sustainable practices become easier to conduct over time or with practice, create spillover benefits, are compatible with landowners' motivations, needs, and goals for their land, develop conservation habits, provide financial benefits, or at least not lead to opportunity costs, and are socially supported (Dayer et al., 2018). CADM + PE considers sources of information, number of employees, years in agriculture, and perceived benefits of the practice. These factors contribute to understanding how the ease of conducting sustainable practices impacts persistence over time, aligning with Dayer's observation that practices becoming easier to conduct can lead to increased persistence. The facilitation of persistence within this framework is contingent upon the nature and tone of information sources and conversational contexts, with employees typically acting as facilitators of habit formation, rendering practices more manageable, while extended experience in agriculture tends to complicate habit formation, attributable to the challenge of altering deeply ingrained practices over time (Dayer et al., 2018). The inclusion of political economic variables in CADM + PE additionally allows for the assessment of spillover effects, such as improved soil structure or reduced opportunity costs associated with sustainable practices, corresponding to Dayer's criterion of spillover benefits contributing to persistence.

In summary, the agreement between this study's findings and Dayer's framework indicates that CADM + PE's comprehensive consideration of political economic variables provides a robust framework for understanding and predicting persistence in sustainable agricultural practices, as it encompasses the factors highlighted by

Dayer and colleagues as critical for persistence. This reinforces the importance of considering a wide range of factors, including political economic variables, when studying behavior change and persistence within agricultural contexts. In encouraging funded practice persistence, governmental and supporting agencies should consider the broad range of factors discussed in CADM + PE when facilitating assistance, targeting not only the beliefs and attitudes of the farmers but also encouraging the building of sustainable habits.

5.2 Contrasting persistence with adoption literature

Adoption and persistence literature in the context of agricultural practices, exhibit significant overlap in their thematic considerations (e.g., Prokopy et al., 2019; Dayer et al., 2018). Both streams of literature emphasize key factors that are crucial for understanding and promoting sustained engagement with new behaviors or practices over time.

One of the central themes shared by adoption and persistence literature is the importance of motivation (Dayer et al., 2018; Ranjan et al., 2019). In adoption literature, motivation plays a critical role in the initial decision-making process, driving individuals to adopt new behaviors or practices (Burton et al., 2008; Ranjan et al., 2019; Reimer et al., 2014). This motivation can stem from various sources such as perceived benefits, incentives, social influences, or personal values and beliefs aligned with the behavior. Similarly, persistence literature recognizes motivation as a key factor in maintaining behavior change over time (Dayer et al., 2018; Frey & Rogers, 2014). Individuals need sustained motivation to continue engaging in the desired behavior, which may evolve from initial experiences, perceived benefits, intrinsic satisfaction, or alignment with personal goals and values. In my models (Table 9) it is clear that the attitude and norm aspects of both RAA and CADM are highly influential on the persistence of practices.

Another shared theme is the role of environmental or contextual factors. Adoption literature often considers how external factors such as social norms, institutional support, policy frameworks, and economic incentives influence the adoption of new behaviors or practices (Prokopy et al., 2008, 2019). These environmental factors create an enabling environment that encourages individuals to initiate behavior change. Similarly, persistence literature acknowledges the impact of environmental factors on behavior maintenance (Dayer et al., 2018; Jackson-Smith et al., 2010; Klöckner & Blöbaum, 2010). Contextual influences, such as social support networks, access to resources, regulatory frameworks, and cultural norms, play a crucial role in sustaining behavior change over time. These factors can either facilitate or hinder the continued engagement with the desired behavior, highlighting their importance in both adoption and persistence processes.

In essence, while adoption literature focuses on the initiation of behavior change and the factors influencing initial adoption decisions, persistence literature extends beyond this by examining the ongoing maintenance and continuity of behavior over time. Despite this difference in focus, the thematic convergence between adoption and persistence literature underscores the interconnectedness of factors that drive behavior change and sustain it over the long term. Both bodies of literature provide valuable insights into the complexities of behavior change processes and highlight the multifaceted nature of promoting sustainable practices in various contexts. Where the foci truly diverge is in the realm of habits.

Habitual processes emerge as a critical determinant of persistence in pro-environmental farming practices, marking a fundamental distinction from factors influencing initial adoption. Kwasnica's (2016) systematic review of maintenance-relevant behavior change theories identifies habits as a crucial component in sustaining behavior change over time. The review highlights that individuals' motivation and cognitive resources play a pivotal role in the initiation and maintenance of behaviors. Initially, individuals are often driven by strong motivators such as enjoyment, satisfaction with outcomes, self-determination, or alignment with personal beliefs and values, which contribute to the initiation of new behaviors. However, as motivation levels fluctuate and cognitive resources become depleted, the need for self-regulatory effort increases to sustain the behavior. This aligns with my modeling wherein habitual processes becoming automatic with repeated performance (see Appendix A for questionnaire questions, Table 9 for models), reduce the reliance on conscious self-regulation and ultimately lead to an increase in persistence. The emphasis on habitual processes in sustaining behavior change diverges significantly from traditional adoption literature. The superiority of CADM-based models acknowledges that sustaining behavior change requires a different set of factors, including habit formation and self-regulation, that influence long-term engagement and adherence to the behavior. In essence, while adoption literature sheds light on the drivers of *initial* change, persistence literature—with its focus on habitual processes—provides insights into the mechanisms that underpin sustained behavior change over time. In promoting the persistence of agricultural practices, program managers and technical assistance providers can leverage the insights derived from these CADM-based approaches, encouraging farmers to integrate new practices into their daily routines to foster habit formation, while developing self-regulation skills enabling them to navigate challenges and setbacks effectively. Facilitating automaticity by making desired practices easy and rewarding promotes sustained engagement while being mindful of contextual factors such as time constraints and financial concerns allows for tailored solutions and the development of farmer support networks. By incorporating these strategies into their technical assistance, providers can significantly enhance farmers' ability to persist in adopting and maintaining sustainable agricultural practices, leading to long-term positive impacts on environmental and agricultural outcomes.

5.3 Variables of note

The regression analysis conducted in this study unveils notable differentiations between RAA and CADM and sheds light on counterintuitive pathways of influence concerning individual political-economic variables.

The comparison between attitudes within RAA and CADM illuminates their divergent roles in behavior change within the realm of sustainable agricultural practices. Both constructs encapsulate cognitive evaluations of behavior outcomes, representing individuals' beliefs regarding the experience of adopting or maintaining specific agricultural practices. However, their respective significances diverge concerning their impact on behavior initiation versus behavior maintenance, offering valuable insights into the nuanced dynamics of behavior change processes.

RAA attitudes—integral to the initiation phase—play a pivotal role in shaping individuals' decisions to adopt new sustainable agricultural practices (Fishbein & Ajzen, 2015). They capture cognitive evaluations, beliefs, and expectations related to the anticipated outcomes associated with these practices. As such, RAA attitudes can act as a sort of barrier to entry, influencing individuals' initial decisions and intentions regarding behavior change. This underscores their significance in understanding the factors that prompt individuals to embark on sustainable agricultural practices, particularly relevant in the early stages of behavior change processes. Conversely, CADM attitudes, while constructed identically in my study to RAA attitudes, may assume a diminished role in behavior maintenance (Kwasnicka et al., 2016). Once individuals have adopted sustainable agricultural practices, other factors such as habit formation, contextual influences, and support mechanisms assume greater significance in sustaining these behaviors over time hence, across models, the diminished statistical significance of attitudes when observing RAA vs CADM-derived models (Dayer et al., 2018). Ultimately, CADM attitudes may not exert the same level of influence on maintaining behavior as they do on initiating it. This shift in the relative importance of attitudes suggests a transition from cognitive deliberation to habitual enactment as behaviors become integrated into individuals' routines and practices (Kwasnicka et al., 2016).

This nuanced transition of significance in models underscores the dynamic nature of behavior change processes, wherein attitudes, particularly within the RAA framework, may serve as critical determinants in the initiation phase, acting as catalysts for behavior change. Meanwhile, as behaviors become established and habitual, the influence of attitudes may wane, giving way to other factors that sustain behavior change in the long term. These findings offer valuable insights into the multifaceted interplay of cognitive, behavioral, and contextual factors in fostering and maintaining sustainable agricultural practices, contributing to a more comprehensive understanding of behavior change dynamics in agricultural settings.

Perceived Behavior Control (PBC), a key construct in RAA often encompasses individuals' perceptions of the ease or difficulty of performing a behavior. However, in the context of behavior persistence, its significance may diminish compared to other factors (Table 9). Research has indicated that while PBC plays a crucial role in behavior initiation, influencing individuals' intentions and motivations, its impact on behavior maintenance and continuity may be less pronounced as PBC shifts to actual control (see AVC in Table 9)(Frey & Rogers, 2014). This is particularly evident in long-term behavior change efforts, where habitual processes, environmental cues, social support networks, and intrinsic motivations tend to exert greater influence on sustained engagement with the behavior (Dayer et al., 2018; Kwasnicka et al., 2016). As behaviors become routinized and integrated into individuals' daily lives, the role of PBC in maintaining behavior may diminish, highlighting the complexity of factors that contribute to behavior persistence over time.

More interesting to note is actual control, which often overshadowed the role of perceived control when looked at in a persistence context. While perceived control, encompassing individuals' beliefs about their ability to perform a behavior, may hold sway in behavior initiation, actual control takes precedence in maintaining behavior over time (Dayer et al., 2018). This distinction becomes evident in research findings, where actual control consistently demonstrates a stronger and more significant influence on behavior persistence compared to perceived control (Table 9)(Klöckner & Blöbaum, 2010). Interestingly, in instances where actual control exhibits statistical significance in my models, it has a positive influence on persistence, indicating that when individuals perceive a higher level of control over their actions, they are more likely to sustain engagement with the behavior (Table 9). While negative in some of the models, AVC is never statistically significant when exerting negative influence on persistence. This underscores the importance of addressing actual control mechanisms, such as access to resources, environmental support, and structural facilitators, in fostering long-term behavior persistence, while also recognizing the nuanced role that perceived control can play in reinforcing persistence when it aligns with actual control capabilities (i.e., seeking out aspects of a farm where control is perceived to be low, e.g. financial or mechanistic capital). Grant programs aimed at fostering sustainable agricultural practices should consider the importance of enabling actual control over behavior change among farms—particularly those with limited financial resources and land holdings. One strategy could involve providing additional technical assistance tailored to the specific needs of such farms, empowering them to implement and sustain environmentally beneficial practices with a more tailored approach for each individual farm (as small farms tend to be more heterogenous). Moreover, there may be a case for increasing grant funding for these farms to offset initial investment barriers (due to the disproportionate effects of equipment costs). Additionally, connecting these farms directly to Community Supported Agriculture or other direct agriculture programs could mitigate financial vulnerability, creating more stable and resilient food system.

CADM habits play a critical role in driving persistence, especially concerning the utilization of soil moisture sensors within the agricultural landscape of larger farms (Table 9). These farms are often perceived to face challenges in sustaining technology adoption due to their scale and longer chain of command structures (Babin et al., 2024; Tan, 2023). CADM habits, however, emerge as a powerful mitigating factor against these barriers; by fostering habitual routines and automated practices, CADM habits may streamline the integration of soil moisture sensors into daily farm operations across the organizational hierarchy. This not only reduces the perceived complexities associated with farm size but also enhances the likelihood of long-term persistence.

The paradoxical finding of lower persistence likelihood associated with seeking information from other farmers, despite its typically positive impact in fostering behavior adoption in other studies, raises intriguing hypotheses (Baumgart-Getz et al., 2012). One plausible explanation could be the phenomenon of an echo chamber within the farming community, where shared experiences and challenges related to a specific event, such as drought during the grant period (as was the case during the grant period in California), create a collective perception of adversity. In such instances, multiple farmers facing similar issues may inadvertently reinforce negative sentiments and concerns about the efficacy or benefits of the practices supported by the grant. This shared experience of hardship and its amplification within the farming community could have contributed to a dampened sense of optimism and commitment to persist with the grant-funded practices. The collective impact of adverse conditions during the grant period may have influenced farmers' perceptions of the practices' effectiveness, potentially leading to a decreased likelihood of persistence despite the positive influence of information from peers typically observed in other contexts.

The negative correlation observed between the number of years in agriculture and behavior persistence aligns with findings from adoption literature and reflects a common trend of unwillingness to change among more experienced individuals in the agricultural sector (Prokopy et al., 2019; Ulrich-Schad et al., 2017). Research in adoption theory often highlights that longer tenures in a particular field can lead to entrenched practices and beliefs, resulting in resistance to adopting new technologies or behaviors. In the context of behavior persistence, this resistance to change may manifest as a reluctance to continue implementing newly adopted practices, especially if they challenge established routines or traditional methods. The negative association between years in agriculture and persistence underscores the need for targeted interventions and strategies to address barriers stemming from entrenched mindsets and the perceived risks associated with adopting novel practices.

The positive correlation observed between the number of employees and behavior persistence underscores the crucial role of resource availability in enabling sustained engagement with adopted practices. Larger teams or more extensive labor resources within agricultural operations can significantly impact persistence by facilitating the implementation and maintenance of new practices (Dayer et al., 2018; Prokopy et al., 2019). The presence of a sufficient workforce allows for more efficient allocation of tasks, better management of workloads, and enhanced capacity to overcome challenges or barriers that may arise during the adoption and continuation of practices. Additionally, a larger workforce can foster a culture of support and collaboration, providing individuals with the necessary assistance, expertise, and motivation to persist with new behaviors. This positive association highlights the importance of resource accessibility, organizational capacity, and team dynamics in promoting behavior persistence within agricultural settings.

The inverse relationship observed between the leased acres ratio and behavior persistence highlights the significance of land tenure arrangements in shaping long-term decision-making processes within agriculture. A higher leased acres ratio, indicating a greater reliance on leased land rather than owned land, is associated with lower levels of persistence of new practices (Table 9). This finding suggests that the stability and security of land tenure can profoundly impact farmers' willingness and ability to make enduring commitments to sustainable practices. Land ownership provides a sense of control, investment, and commitment to the land, fostering a long-term perspective that encourages persistence with adopted behaviors (Reimer et al., 2012). In contrast, leasing arrangements, which may lack the same level of security or investment, can introduce uncertainties and constraints that diminish the likelihood of sustained engagement with new practices (Bigelow et al., 2016; Ranjan et al., 2022). The waning of funding resources can engender a decline in motivation for sustained agricultural practices, attributed to the diminished incentives for land stewardship motivators . This phenomenon underscores the intricate interplay between financial incentives and long-term commitment to land management. When external funding sources diminish, the intrinsic motivations and benefits associated with maintaining one's land may become insufficient to sustain the desired level of engagement. This underscores the importance of considering land tenure dynamics and their implications for decision-making and behavior persistence in agricultural contexts. Technical assistance providers can significantly enhance their support for landowners with precarious tenure arrangements by implementing a more involved approach to support, involving capacity-building initiatives aimed at equipping landowners with the skills and knowledge necessary to implement and sustain funded practices effectively. Additionally, fostering peer learning networks among landowners facing similar tenure challenges can be instrumental in promoting knowledge exchange, collaboration, and collective problem-solving (Asprooth et al., 2023; Lavoie & Wardropper, 2021; Pape & Prokopy, 2017). These networks provide valuable opportunities for shared experiences, best practices, and mutual support, further enhancing practice persistence and innovation. Establishing consistent communication channels, regular follow-ups, and ongoing monitoring of progress allows providers to offer continuous guidance, address emerging challenges, and adapt strategies as needed. This long-term engagement fosters trust, builds relationships, and reinforces commitment, leading to more successful outcomes in practice sustainability. Furthermore, extending funding periods for landowners with precarious tenure arrangements is crucial in ensuring the financial stability and continuity of funded practices. Longer funding durations provide landowners with greater certainty and flexibility, reducing the risk of discontinuity and incentivizing long-term investment in sustainable land management. By combining capacity building, peer learning networks, long-term engagement, and extended funding periods, agricultural technical assistance providers can effectively target and support landowners in persisting with funded practices, ultimately contributing to improved agricultural sustainability and resilience.

5.4 Future Research

The insights gained from examining factors influencing behavior persistence in agriculture hold several implications for future research endeavours. Firstly, the findings underscore the need for a nuanced understanding of the interplay between individual beliefs, contextual factors, and environmental conditions in shaping behavior persistence. Future studies could delve deeper into the mechanisms through which habitual processes, resource availability, land tenure arrangements, and social influences interact to either facilitate or hinder persistence with adopted practices. Future research could additionally conduct an in-depth exploration of the psycho-social dynamics underlying habit formation in the context of agricultural practice persistence, employing qualitative studies to investigate the process by which habits become deeply entrenched and exploring potential strategies to enhance and accelerate this habituation process. Secondly, the contrasting roles of perceived control, actual control, and information from peers highlight the complexity of factors influencing behavior persistence. Further research could explore how these factors dynamically evolve over time and under varying circumstances, particularly in response to external shocks or changes in environmental conditions.

Additionally, the influence of tenure in agriculture, as evidenced by the leased acres ratio, suggests the importance of considering broader socio-economic factors in understanding persistence. Future studies could investigate how policy interventions, land tenure reforms, and economic incentives impact farmers' decision-making processes and their ability to sustainably adopt and maintain practices over the long term.

Moreover, the role of peer networks and information exchange in shaping attitudes and behaviors warrants further investigation. Understanding the dynamics of information diffusion, social learning, and peer influence could provide valuable insights into strategies for promoting behavior persistence through targeted communication, community engagement, and collaborative networks. Overall, future research should aim to build upon these findings by adopting interdisciplinary approaches, incorporating longitudinal studies, and exploring innovative methodologies to comprehensively unravel the complexities of behavior persistence in agriculture. Such efforts are essential for developing tailored interventions, policy recommendations, and practical solutions that foster sustainable agricultural practices and resilience in the face of evolving challenges.

5.5 Limitations

Despite its contributions, this study faces several limitations that warrant consideration. Firstly, the research focused exclusively on behavior persistence within the framework of Office of Environmental Farming Innovation grants, potentially limiting the generalizability of the findings to other agricultural incentive programs or sectors. This narrow scope may overlook variations in behavior persistence across diverse agricultural contexts, necessitating caution in extrapolating the results beyond

OEFI grant recipients. Secondly, the study's exclusive emphasis on OEFI—which tends to support larger-than-average farms—may constrain the applicability of the findings to smaller-scale agricultural operations or farms with different structural characteristics (Babin et al., 2024). While insights gained from larger farms are valuable, they may not fully capture the experiences and challenges encountered by smaller or differently structured farms, highlighting the need for future research to encompass a broader spectrum of agricultural settings.

Moreover, the analytical approach—logistic regression— may be perceived as less robust compared to advanced techniques like structural equation modeling (SEM) which are better suited to validate theoretical frameworks. While regression analysis offers valuable insights, SEM provides a more comprehensive understanding of complex relationships and causal pathways, which could enhance the depth of analysis in studying behavior persistence in agriculture. Lastly, the study's reliance on the Comprehensive Action Determination Model underscores the importance of further developing and refining CADM questions specifically tailored to agricultural research contexts. Customizing CADM questions to capture the unique motivations, challenges, and behavioral determinants relevant to agricultural practices could enhance the study's validity and reliability in assessing behavior persistence accurately.

Addressing these limitations in future research endeavors could strengthen the methodological rigor, broaden the applicability of the findings, and advance our understanding of behavior persistence within diverse agricultural landscapes.

5.6 Conclusion.

This study investigated the determinants of behavior persistence within the agricultural context, focusing on the adoption and continuation of sustainable practices among larger farms participating in OEFI grants. Utilizing the Comprehensive Action Determination Model, the Reasoned Action Approach, and logistic regression analysis, the research revealed valuable insights into the factors influencing behavior persistence in agriculture. The findings highlighted the significant role of CADM habits, resource availability, land tenure arrangements, and social influences in shaping behavior persistence. CADM habits emerged as a crucial driver, facilitating the integration of new practices into daily operations and mitigating barriers associated with farm size and management structures. Additionally, the positive influence of resource availability, particularly in terms of workforce capacity, underscored the importance of organizational support in fostering long-term engagement with sustainable practices.

Despite limitations, this study contributes valuable insights into understanding the complexities of behavior persistence in agriculture. By addressing these limitations in future research, such as expanding the scope to diverse agricultural sectors, employing advanced analytical methods, and refining measurement tools, we can advance our understanding and develop more effective strategies for promoting sustainable behavior change and innovation in agricultural practices.

In conclusion, this research lays a foundation for ongoing dialogue and exploration aimed at fostering resilience, sustainability, and long-term success in the agricultural sector, ultimately contributing to the advancement of agricultural sustainability and environmental stewardship.

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Appendices

Appendix A. HSP Survey

Cal Poly and the California Department of Food and Agriculture are conducting this survey in order to evaluate the impact and effectiveness of the Healthy Soils Program (HSP). If you received a HSP grant we'd greatly appreciate your input.

The benefits of your voluntary completion of this survey include:

- A $20 eGift card.
- Helping improve the HSP program.
- Voicing the needs, concerns, and achievements of California farmers.

This survey includes questions about your personal experiences and opinions and takes approximately 20 minutes to complete. You may skip any questions you choose not to answer. There are no anticipated risks with your participation in this study, as any information you provide is confidential and will not be linked to your name or company.

If you have questions regarding this study or would like to be informed of the results when the study is completed, please contact Dr. Babin at 805-756-2373, nbabin@calpoly.edu. If you have any concerns about the conduct of the research project or your rights as a research participant, you may contact Dr. Michael Black, Chair of the Cal Poly Institutional Review Board, at (805) 756-2894, mblack@calpoly.edu, or Ms. Trish Brock, Director of Research Compliance, at (805) 756-1450 or pbrock@calpoly.edu.

If you are 18 years of age and agree to voluntarily participate in this research project as described, please indicate your agreement by clicking “I agree” below. You may stop and quit the survey at any time but your $20 eGift card will only be disbursed if you complete the survey. If you are not 18 years of age or would not like to participate, please click “I disagree”.

Were you awarded more than one Healthy Soils Program (HSP) grant between 2018-2020?

How many HSP grants were you awarded between 2018-2020?

When responding to the rest of the survey, please sum together the practices implemented, and your overall experiences with them, across your different HSP awards between 2018-2020.

What year was your Healthy Soils Program (HSP) project funded?

2018, 2019, 2020, Unsure/ Don't remember

What is the status of your project?

Completed, Will complete in 2023, Will complete in 2024

For each HSP practice listed below (Cover crops, Compost, Hedgerows, Mulching, Reduced-till, No-till) please read all four questions and check the box when the answer is yes.

1. *Was this practice included in your HSP project?*
2. *Do you currently use this practice on your farm?*
3. *Do you intend to use this practice in the next 12 months?*
4. *Do you intend to **expand** the area dedicated to this practice in the next 12 months?*

For each group of HSP practices listed below (**In-field practices**: Nutrient management, range planting, pasture and hay planting, prescribed grazing, conservation crop rotation, strip cropping, whole orchard recycling; **Edge of field practices**: Conservation cover, riparian forest buffer, silvopasture, windbreak/shelterbreak establishment, riparian herbaceous cover, tree/shrub establishment, multi-story cropping, herbaceous wind barrier, grassed waterway, field border, filter strip, contour buffer strip), read each question 1-4 and check the box if the answer is yes.

1. *Were any of these practices included in your HSP project?*
2. *Do you currently use any of these practices on your farm?*
3. *Do you intend to use any of these practices in the next 12 months?*
4. *Do you intend to expand the area dedicated to any of these practices in the next 12 months?*

As a result of my HSP project ____ (true or false)

1. *I have gained new knowledge and experience about the management of healthy soils.*
2. *I have implemented other conservation practices not funded by my project.*
3. *I have applied for other grants to fund conservation practices on my farm.*
4. *My farming network has expanded.*
5. *I have received preferential treatment from buyers and/or processors.*
6. *I have received a price premium for my crops.*

Please indicate your level of agreement or disagreement with the following statements. (5 point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *Improving soil health is an urgent problem for agriculture.*
2. *This project has improved public perception of my agricultural operation.*
3. *Programs like the HSP are important for improving the public's perception of agriculture.*
4. *My farm is more resilient following the HSP project.*
5. *I would recommend my HSP practices to a friend.*

The HSP program requires annual soil sampling to monitor soil organic matter (SOM) pools. What did your soil samples reveal about the level of SOM in your HSP-funded project area?

SOM increased over time, SOM decreased over time, SOM did not change over time, SOM fluctuated up and down, Unsure/ Don't remember

Have you talked with other growers about your experiences with the HSP?

No, Yes, Unsure/Don't remember

About how many people have you spoken with about your experience?

Do you think that your project has had a significant impact on the adoption of healthy soils practices by other growers?
No, Yes, Unsure/Don't remember

About how many growers do you estimate have adopted healthy soils practices, at least partially because of your project?

CDFA contracts Technical Assistance Providers (TAPs) to provide free support to HSP grant recipients. These TAPs are often based out of Resource Conservation Districts, UC Cooperative Extension offices, and nonprofit organizations. Did you work with a TAP at any time during your HSP Project?

No, Yes, Unsure/Don't remember

Check all boxes in which TAPs offered support to your HSP project.

Exploration: Explaining the HSP program and application process. Exploring the technical attributes of HSP practices

Proposal: Vision and design of HSP project scope. Writing and submission of the HSP grant application.

Implementation: Selecting plants/seeds and other supplies. Coordinating with vendors and regulators. Installation and troubleshooting of HSP practices after implementation.

Reporting: HSP mandated soil sampling. Reporting and invoicing to CDFA

Other (please specify)

How important was TAP support in carrying out your HSP project?

Not at all important, Slightly important, Moderately important, Very important, Extremely important

In this section, we will assess your experience with the cover crops included in your HSP project.

Was this HSP project your first experience managing cover crops on your farm?

No, Yes

How many years of experience did you have with cover crops prior to your HSP project?

During which three-year time period were cover crops planted as part of your HSP project?

2018-2020, 2019-2021, 2020-2023, 2021-2024, Other period (please specify:)

How many acres of cover crops were included in your HSP project?

About how many ***total*** acres of cover crops were planted on your farm in each of the following years?

2021 acres, 2022 acres, 2023 (planned acres)

Expand In the next five years, will you expand the total acreage of cover crops planted on your farm?

Definitely not, Probably not, Might or might not, Probably yes, Definitely yes

Which of the following statements best reflects your attitude towards cover crops before this HSP project.

Prior to this project I was unsure about the value of cover cropping for my farm.

Prior to this project I was already convinced that cover crops were a valuable practice for my farm.

Which of the following three statements best reflects the impact of the HSP program on your decision to maintain cover cropping after the three-year incentive period has ended?

This project convinced me to maintain cover crops after the incentive payments end., This project convinced me not to maintain cover crops after the incentive payments end., I am still uncertain whether I will maintain cover crops after the incentive payments end.

Which of the following three statements best reflects the impact of the HSP program on your decision to maintain cover cropping after the three year incentive period has ended?

This project reinforced my commitment to maintain cover crops after the incentive payments end., This project convinced me not to maintain cover crops after the incentive payments end., This project has made me uncertain whether I will maintain cover crops after the incentive payments end.

If HSP financial incentives had continued for two additional years would you have been more likely to maintain cover cropping?

No, Yes, Unsure/don't know

In 2018, HSP paid $126/acre for single-species cover crops and $147/acre for multiple-species cover crops. Please use the slider to indicate what you would consider a fair payment rate for cover cropping on your farm.

(Option also given for: Not Applicable- The HSP price was fair enough.)

The following farming conditions are often impacted by cover cropping. Please rate what type of an impact you have seen from cover crops on your farm (5 point Likert: Significant harmful impact, Minor harmful impact, No impact/ unsure, Minor beneficial impact, Significant beneficial impact)

Soil Structure, Water Infiltration, Water Holding Capacity, Erosion, Weeds, Pollinators, Pest and Disease Control, Other (please specify):

Please fill in the blank: My using cover crops in the next 12 months would be_________.
Very harmful for my farm, Somewhat harmful for my farm, Neither beneficial or harmful for my farm, Somewhat beneficial for my farm, Very beneficial for my farm

How has cover cropping impacted your use of herbicides?

I apply less herbicides, I apply about the same amount of herbicides, I apply more herbicides

How have cover crops impacted your use of tillage?

I use less tillage, I use about the same amount of tillage, I use more tillage

Please fill in the blank: My using cover crops in the next 12 months would be________.
Very unenjoyable for me, Somewhat unenjoyable for me, Neither enjoyable nor unenjoyable for me, Somewhat enjoyable for me, Very enjoyable for me

Please indicate your level of agreement or disagreement with the following statements: (5-point Likert, Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *My decision to use cover crops in the next 12 months is completely up to me.*
2. *Most people whose opinions I value would approve of me using cover crops in the next 12 months.*
3. *Most farmers like me will use cover crops in the next 12 months.*
4. *Most farmers I respect and admire will use cover crops in the next 12 months.*

Which of the following four statements best reflects your experience with cover cropping?

The use of cover crops has enabled me to reduce my crop fertility inputs over time and still meet the needs of my cash crop., The use of cover crops has not impacted my cash crop fertility program., The use of cover crops has required me to use additional crop fertility inputs over time to meet the needs of my cash crop., I have never investigated the fertility benefits of cover crops on my farm.

What has been the overall impact of cover cropping on profitability of your operation?

Moderate decrease in net profit (5% or more decrease), Minor decrease in net profit (2-4% decrease), No significant change in net profit (plus or minus 1% change in net profit),minor increase in net profit (2-4% increase), Moderate increase in net profit (5% or more increase), I am not measuring economic outcomes

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert, Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *I have the knowledge and technical skills to successfully cover crop over the next 12 months.*
2. *I have the labor and equipment resources to successfully cover crops over the next 12 months.*
3. *Environmental factors (water availability, rainfall timing, temperatures, etc.) will impact my decision to use cover crops over the next 12 months.*
4. *Cover crops pay for themselves and are worth doing even in the absence of incentives.*
5. *I would have eventually adopted cover crops on my HSP project fields without CDFA funding.*
6. *I would have benefited from more technical assistance in implementing cover crops.*

The following are some challenges that growers often experience when using cover crops. Please rate how challenging each issue has been for management of the cover crops planted as part of your HSP project. (5-point Likert, Not challenging at all, Slightly challenging, Moderately challenging, Very challenging, Extremely challenging)

1. *Poor germination and establishment of cover crop.*
2. *Cover crop competition with cash crop for water.*
3. *Cover crop termination delays planting of cash crop.*
4. *Other (please specify):*

How much control do you have over your use of cover crops in the next 12 months.

None at all, A little, A moderate amount, A lot, A great deal

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert, Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *It would be difficult to manage my farm without cover crops.*
2. *Cover crops are now part of my farm management routine.*
3. *Cover crops no longer require much thought to implement and manage.*
4. *I like the way that cover crops make my fields look.*
5. *Leaving soil bare and without cover crops hinders the optimal operation of my farm.*
6. *Planting cover crops protects my farm's soil.*
7. *In my experience with cover crops, the benefits outweigh the costs.*

Please fill in the blank: For me to use cover crops in the next 12 months will be_______.
Extremely difficult, Somewhat difficult, Neither easy nor difficult, Somewhat easy, Extremely easy

In this section, we will evaluate your experiences with compost in your HSP project.

Was this HSP project your first experience applying compost on your farm?

No, Yes

How many years of experience did you have with compost prior to your HSP project?

Over what three year time period did you apply compost as part of your HSP project?

2018-2020, 2019-2021, 2020-2023, 2021-2024, Other period (please specify):

How many acres did you apply compost to as part of your HSP project?

About how many ***total*** acres of compost were applied on your farm in each of the following years?

1. *2020*
2. *2021*
3. *2022*
4. *2023 (planned)*

In the next five years, will you expand the total acreage where compost is applied on your farm?

Definitely not, Probably not, Might or might not, Probably yes, Definitely yes

Which of the following statements best reflects your attitude towards compost application before this HSP project.

Prior to this project I was uncertain about the value of compost applications for my farm., Prior to this project I was already convinced that compost application was a valuable practice for my farm.

Which of the following three statements best reflects the impact of the HSP program on your decision whether to maintain compost applications after the three-year incentive period has ended?

This project convinced me to maintain compost applications after the incentive payments end., This project convinced me not to maintain compost applications after the incentive payments end., I am still uncertain whether I will maintain compost applications after the incentive payments end.

Which of the following three statements best reflects the impact of the HSP program on your decision whether to maintain compost applications after the three-year incentive period has ended?

This project reinforced my commitment to maintain compost applications after the incentive payments end., This project convinced me not to maintain compost applications after the incentive payments end., This project has made me uncertain whether I will maintain compost applications after the incentive payments end.

If HSP financial incentives had continued for two additional years would you have been more likely to maintain compost applications?

No, Yes, Unsure/Don't Know

The HSP payment rate for compost application was $50 per ton.

Please use the slider to indicate what you believe to be a fair HSP payment rate for the initial three year trial of compost application on your farm.

HSP compost application rates varied between 2-8 tons per acre depending upon crop type and compost composition.

What was the compost application rate utilized in your HSP project fields?

(Option given: Unsure)

What do you believe would have been an optimal compost application rate for your HSP project fields?

(Option given: Unsure/ Don't remember)

How did you apply your compost?
Spread it using equipment and labor from my farming operation, Hired someone outside my farming operation, Other (please specify):

Do you currently produce compost on your farming operation?

No, Yes

This project led me to consider producing more of my own compost.
No, Yes

This project has led me to consider producing my own compost in the future.

No, Yes

How much do food safety concerns impact your ability to use compost?
None at all, A little, A moderate amount, A lot, A great deal

Which of the following four statements best reflects your experience with compost?

The use of compost has enabled me to reduce my crop fertility inputs over time and still meet the needs of my cash crop., The use of compost has not impacted my cash crop fertility program., The use of compost has required me to use additional crop fertility inputs over time to meet the needs of my cash crop., I have never investigated the fertility benefits of compost on my farm.

Please fill in the blank: My using compost in the next 12 months would be_________.

Very harmful for my farm, Somewhat harmful for my farm, Neither beneficial or harmful for my farm, Somewhat beneficial for my farm, Very beneficial for my farm

The following farming conditions are often impacted by composting. Please rate what type of an impact you have seen from compost application on your farm. (5-point Likert, Significant harmful impact, Minor harmful impact, No impact/unsure, Minor beneficial impact, Significant beneficial impact)

1. *Soil Structure*
2. *Water Infiltration*
3. *Water Holding Capacity*
4. *Erosion*
5. *Weeds*
6. *Pollinators*
7. *Pest and Disease Control*
8. *Other (please specify):*

About how long did it take for you to begin seeing soil benefits on your farm from using compost?

(Option given: I have seen no benefits)

How has compost application impacted your use of tillage?

Less tillage, About the same amount of tillage, More tillage

Please fill in the blank: My using compost in the next 12 months would be_______.

Very unenjoyable for me, Somewhat unenjoyable for me, Neither enjoyable nor unenjoyable for me, Somewhat enjoyable for me, Very enjoyable for me

Please indicate your level of agreement or disagreement with the following statements: (5-point Likert, Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *Most people whose opinions I value would approve of me using compost in the next 12 months.*
2. *Most farmers like me will use compost in the next 12 months.*
3. *Most farmers I respect and admire will use compost in the next 12 months.*

What has been the overall impact of compost on profitability of your operation?

Moderate decrease in net profit (5% or more decrease), Minor decrease in net profit (2-4% decrease), No significant change in net profit (plus or minus 1% change in net profit), Minor increase in net profit (2-4% increase), Moderate increase in net profit (5% or more increase), I am not measuring economic outcomes

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree).

1. *I have the knowledge and technical skill to successfully manage compost application over the next 12 months.*
2. *I have access to sufficient labor and equipment to successfully manage compost applications over the next 12 months.*
3. *Environmental factors (water availability, rainfall timing, temperatures, etc.) will impact my decision to apply compost over the next 12 months.*
4. *Compost application pays for itself and is worth doing even in the absence of incentives.*
5. *I would have applied compost on my HSP project fields without CDFA funding.*
6. *I would have benefited from more technical assistance surrounding compost application.*

The following are some challenges that growers often experience when using compost. Please rate how challenging each issue has been for compost application on your farm. (5-point Likert, Not challenging at all, Slightly challenging, Moderately challenging, Very challenging, Extremely challenging)

1. *Difficulties acquiring quality compost*
2. *Difficulties finding certified compost*

3. *Difficulties transporting and/ or spreading compost*
4. *Other (please specify):*

How much control do you have over your use of compost in the next 12 months.

None at all, A little, A moderate amount, A lot, A great deal

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *It would be difficult to manage my farm without compost.*
2. *Compost application is now part of my farm management routine.*
3. *Compost application no longer requires much thought to implement and manage.*
4. *I like the way that compost make my fields/soils look.*
5. *Using chemical fertilizers hinders the optimal operation of my farm.*
6. *Applying compost protects my farm's soil resources.*
7. *In my experience with compost, the benefits outweigh the costs.*

Please indicate your level of agreement or disagreement with the following statement. The HSP funded compost was a temporary substitute for the chemical fertilizer inputs that I have reverted to following the completion of the three year trial.

Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree

Please fill in the blank: For me to use compost in the next 12 months will be_____.

Extremely difficult, Somewhat difficult, Neither easy nor difficult, Somewhat easy, Extremely easy

Earlier in the survey you indicated that your HSP project featured Edge of field (EoF) practices. EoF practices refer to plantings or structures which support the delivery of key ecosystem services like soil stabilization, water filtration, carbon storage and pollinator and wildlife habitat.

The HSP recognized EoF practices include: hedgerow planting, conservation cover, riparian forest buffer, range planting, silvopasture, windbreak/shelterbreak establishment, riparian herbaceous cover, tree/shrub establishment, multi-story cropping, herbaceous wind barrier, grassed waterway, field border, filter strip, and contour buffer strip.

In this section we will be asking you questions about your experiences with EoF practices.

Was this HSP project your first experience with EoF practices on your farm?

No, Yes

How many years of experience did you have with EoF practices prior to your HSP project?

How many acres of EoF practices were included in your HSP project?

In the next five years, will you expand the total acreage dedicated to EoF practices on your farm?

Definitely not, Probably not, Might or might not, Probably yes, Definitely yes

Please fill in the blank: Maintenance of my EoF practice in the next 12 months would be_____.
Very harmful for my farm, Somewhat harmful for my farm, Neither beneficial or harmful for my farm, Somewhat beneficial for my farm, Very beneficial for my farm

The following farming conditions are often impacted by EoF practices. Please rate what type of an impact you have seen from EoF practices on your farm. (5-point Likert, Significant harmful impact, Minor harmful impact, No impact/unsure, Minor beneficial impact, Significant beneficial impact)

1. *Soil Structure*
2. *Erosion*
3. *Water Infiltration*
4. *Water Quality*
5. *Wind Damage*
6. *Weeds*
7. *Pollinators*
8. *Pest and Disease Control*
9. *Wildlife (quail, pheasants, etc.)*
10. *Other (please specify):*

About how long did it take for you to begin seeing benefits on your farm from EoF practices? *(Option given: I have seen no benefits)*

Please fill in the blank: Maintenance of my EoF practice in the next 12 months would be_____.
Very unenjoyable for me, Somewhat unenjoyable for me, Neither enjoyable nor unenjoyable for me, Somewhat enjoyable for me, Very enjoyable for me

Please indicate your level of agreement or disagreement with the following statements: (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *My decision to maintain my EoF practice in the next 12 months is completely up to me.*
2. *Most people whose opinions I value would approve of me maintaining my EoF practice in the next 12 months.*
3. *Most farmers like me will use EoF practices in the next 12 months.*
4. *Most farmers I respect and admire will use EoF practices in the next 12 months.*
5. *The HSP payment for EoF practices was sufficient.*

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *I have the knowledge and technical skill to manage my EoF practices over the next 12 months.*
2. *I have access to sufficient labor and equipment to manage my EoF practices over the next 12 months.*
3. *Environmental factors (water availability, rainfall timing, temperatures, pest concerns etc.) will impact my decision to maintain my EoF practices over the next 12 months.*
4. *EoF practices pay for themselves and are worth doing even in the absence of incentives.*
5. *I would have implemented the EoF practices specified in my HSP project without CDFA funding.*
6. *I would have benefited from more technical assistance surrounding EoF practices.*

The following are some challenges that growers often experience with EoF practices. Please rate how much of a challenge these issues have been for you in managing EoF practices. (5-point Likert, Not challenging at all, Slightly challenging, Moderately challenging, Very challenging, Extremely challenging)

1. *Cost of maintenance.*
2. *Loss of cropland.*
3. *Issues with plant establishment and survival.*
4. *Increased fire risk.*
5. *Food safety concerns.*
6. *Not owning the land that I farm.*
7. *Other (please specify):*

How much control do you have over your maintenance of your EoF practice in the next 12 months.

None at all, A little, A moderate amount, A lot, A great deal

Please indicate your level of agreement or disagreement with the following statements. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *It would be difficult to manage my farm without my EoF practice.*
2. *EoF practices are now part of my farm management routine.*
3. *EoF practices no longer require much thought to implement and manage.*
4. *I like the way that EoF practices make my farm*
5. *Maintaining my EoF practices protects my farm's soil.*
6. *Maintaining my EoF practices supports local biodiversity.*
7. *In my experience with EoF practices, the benefits outweigh the costs.*

Please fill in the blank: For me to maintain my EoF practice in the next 12 months will be______.

Extremely difficult, Somewhat difficult, Neither easy nor difficult, Somewhat easy, Extremely easy

Many of the practices funded under the Healthy Soils Program have impacts on native biodiversity. In the following questions, we would like to learn more about how you manage non-crop native species on your farm and how you think about your farm system.

Do you manage for the following types of native biodiversity? (2 Options, Yes, I do., No, I don't.)

1. *Plant species (e.g. oaks, wildflowers)*
2. *Pollinator species (e.g., bees, bats, songbirds)*
3. *Game species (e.g., duck, deer, elk)*
4. *Endangered species (e.g., Monarch butterflies, California Tiger Salamander)*
5. *Other (Please specify):*

In 1-2 sentences, please describe why you do or do not manage for the species included in the previous question.

Please indicate your level of agreement or disagreement with the following statements about biodiversity. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *I am concerned about the potential impacts of biodiversity loss on my farm.*
2. *I consider biodiversity an important part of my farm.*
3. *I consider biodiversity an important part of my farm.*
4. *The risks of implementing biodiversity practices on my farm (e.g. food safety and endangered species concerns) outweigh the benefits.*

Please indicate your level of agreement or disagreement with the following statements about farm systems management. (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *When I make decisions on my farm, I tend to see all kinds of possible consequences for each decision.*
2. *By making plans and controlling my farm operations, I can accurately predict how successful my farm operation will be.*
3. *When I have problems on my farm, I think about how I can change my operations to help reduce those problems in the future.*
4. *I always look at the interconnections and mutual influences between all the decisions that go into my farm management.*
5. *I think continuously about how to improve my farm operations.*

Please select your single most important motivation for participating in the HSP.
Improve soil health, Improve yields, Reduce external input costs, Improve water quality, Sequester carbon to mitigate climate change, Support biodiversity, Adapt to a changing climate, Other (Please specify)

Adoption of conservation practices is often motivated by a desire to manage risk. How concerned are you about the impact of the following risks on the viability of your farming operation? (5-point Likert, Not at all concerned, Slightly concerned, Somewhat concerned, Moderately concerned, Extremely concerned)

1. *Market oversupply and low crop prices*
2. *Inflation and rising business costs*
3. *Labor availability*
4. *Regulations*

5. *Land access and price*
6. *Food safety liability*
7. *Water supply*
8. *Weather volatility*
9. *Diseases and pest*

People get information about soil health from a number of different sources. How often do you use the following sources of information about soil health? (4 options, Never, Rarely, Sometimes, Often)

1. ***Ag media:*** *Magazines, radio, TV, social media, podcasts, etc.*
2. ***Private consultants:*** *Certified crop advisors, pest control advisors, farm management companies*
3. ***Governmental sources:*** *Resource Conservation Districts, UC Cooperative Extension, USDA NRCS, CDFA*
4. ***Non-governmental organizations:*** *American Farmland Trust, CalCan, Farm Bureau*
5. ***Other farmers***

In this section we will be asking about the application process and your experience with CDFA administration of HSP grants.

Did anyone help you with your HSP program application?

No, Yes, Unsure/Don't remember

Select all that helped with the application process. *Co-worker/employee, Company/developer/vendor/consultant, HSP Technical Assistance Provider, Family member, Friend, Another farmer, Other (please specify):*

Based on your experience with the CDFA climate-smart application process, please provide your opinions on the following statements (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *The application was clear and easy to understand.*
2. *The application window (time between solicitation issued and application deadline) was too short.*
3. *I reduced the complexity/ number of practices in my application in order to submit on time.*
4. *I had difficulty acquiring supporting information like bids and tests in a timely manner.*
5. *The lag between initial project approval and contract signing hindered optimal project implementation.*

Based on your experience with the CDFA climate-smart application process, please provide your opinions on the following statements (5-point Likert Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree)

1. *My invoices were paid in a timely manner.*
2. *The CDFA program staff assigned to my project responded to questions and requests in a timely manner.*
3. *The CDFA program staff assigned to my project were professional and knowledgeable.*
4. *This project improved my perception of CDFA.*
5. *I would apply to this program again, knowing what I know now.*

Did your project feature a budget change?
No, Yes, Unsure/Don't remember

Did you feel the budget change process was overly complicated and hindered the timely completion of your project?
No, Yes

Did your CDFA contact person change over the course of the project?

No, Yes, Unsure/Don't remember

Did changing your CDFA contact person negatively impact your experience with the HSP?

No, Yes

Did you obtain a portion of your funding before yabour project began?
No, Yes, Unsure/Don't remember

What percentage of the funding did you obtain before your project began?

Would you have liked more funding available before your project began?

No, Yes

How much funding would you have liked to be available before your project began?

How many times did you apply for an HSP grant before receiving funding?

In this final section, we ask you a few questions about yourself and your farming operation. This demographic information helps us understand the makeup of who responded to this survey, which helps give a fuller picture of what groups participate and what voices may be missing in our data. *Please note you may skip any question in this section you do not want to answer.*

What year were you born?

What is your gender identity?

Male, Female, Non-binary, Prefer not to say, Prefer to self specify

Do you belong to any of the following CDFA-designated socially disadvantaged groups? Please check all that apply.

Hispanic, Asian American, African American, Native American/American Indian (Specify if desired), Alaskan Native (Specify if desired), Native Hawaiian and Pacific Islanders (Specify if desired), None of the above/ prefer not to say

How many total acres is your farming operation? Please estimate how many of these acres are owned versus leased from others.

1. *Total Acres*
2. *Acres Leased*
3. *Acres Owned*

How many total acres were included in your HSP project?

How many acres of your HSP project were on leased land?

What is your farm's principal crop type.

Fruits and nuts, Mixed vegetables and berries, Field crops: cotton, alfalfa, grains (corn, rice, beans, winter wheat, etc.), Grazing pasture, Grape vineyards, Mixed (at least 25% of multiple of the above crop types)

Please select the county where the majority of your HSP project occurred.

What was your net household income from agriculture in 2022? *If you prefer not to respond you may skip to the next question.*

What were your gross receipts from farming in 2022? *If you prefer not to respond you may skip to the next question.*

Approximately what proportion of your total household income comes from agriculture?

What is the highest level of school you have completed? *Some formal schooling, High school diploma / GED, Some college, 2-year college degree, 4-year college degree, Graduate/professional degree*

How long have you worked in agriculture?

How many full-time employees does your farming operation employ?

Were any of the lands utilized for the HSP project certified Organic?

No, Yes

Were any of the lands utilized for the HSP project certified by the Leafy Greens Handler Marketing Agreement (LGMA)?

No, Yes

Please estimate the average annual rainfall at your HSP project site (inches).

What percentage of the croplands you manage are irrigated?

What percentage of this irrigation is from groundwater?

Did your HSP project take place on farmland located in a SGMA regulated basin?

No, Yes, Unsure/Don't know

What type of contract best characterizes the majority of your agricultural production?
No contract for the 2023 harvest, Contract secured for the 2023 harvest, Contract secured for the 2023 and 2024 harvests, Contract secured of the next three harvests or more (at least through 2025), Unsure/Don't know

What is the most important market for your agricultural production?
Wholesale, Online, Farm stand, Community supported agriculture, Direct sales to institutions (restaurants, schools, hospitals, etc.), Farmers markets, Other (please specify):, Unsure/Don't know

Please use the box below to share any additional comments about the HSP program or survey.

Appendix B. Coding Framework

For ease of data cleaning, I have turned the question output from Qualtrics into a series of codes. They are separated by underscores for ease of analytical software reading, sorry it's a bit ugly. Below you will find what most questions output should be, they are meant to easily be able to refer back to the survey and know the exact wording of the question. Aspects of the question output that are in parenthesis are optional to the code depending on where the question is. The number of letters should be the number of letters in the question output.

Question Output:

General Questions: A(_E)_X(_N)(.N)
Practice Questions: A_BB_(E_)X(.N)
Theory Questions: A_BB_CCC(C)_DD(D)_N
Biodiversity and Systems Thinking Questions: A_CC(_E)_X(.N)

Question Type Examples:

General Question: H_R_Gain_Knowledge
HSP, Results Matrix, Gained Knowledge
As a result of my HSP project I have gained knowledge about the management of healthy soils.
Practice Question: H_CP_B_Soil_Structure
HSP, Compost, Benefits Matrix, Soil Structure
Measuring benefits to soil structure from compost in the HSP grant.
Theory Question: H_CP_RAA_EA_1
HSP, Compost, Reasoned Action Approach, Experiential Attitudes, 1st Q
Please fill in the blank: My using compost in the next 12 months would be_______. [Refer to original codebook]
Biodiversity and Systems Thinking Question:
H_BD_P_In_Field
HSP, Biodiversity, Practice Matrix, In Field
Asks if they use in field practices to manage for biodiversity.

Code Book:

A: Survey Prefix

A: *AMMP*
D: *DDRDP*
H: *HSP*

S: *SWEEP*

B: Practice Code

AM: *Alternative Manure*
CB: *Compost Bedded Pack Barn*
CC: *Cover Crops*
CP: *Compost*
DD: *Dairy Digester*
EF: *Edge of Field*
FS: *Flush to Scrape Manure Collection System*
FW: *On-Farm Weather Station*
IS: *Irrigation Subscription*
SL: *Solar*
SM: *Soil Moisture Monitoring*
SS: *Solid Separation System*

C: Theory Code

BD: *Biodiversity*
CADM: *Comprehensive Action Determination Model*
RAA: *Reasoned Action Approach*
ST: *Systems Thinking*

D: Construct Code

AC: *Awareness of Consequences*
AN: *Awareness of Needs*
BI: *Behavioral Intentions (CADM Intentional Processes)*
IA: *Instrumental Attitudes (CADM Intentional Processes)*
EA: *Experiential Attitudes (CADM Intentional Processes)*
IN: *Injunctive Norms (CADM Personal Norms)*
DN: *Descriptive Norms (CADM Social Norms)*
PBC: *Perceived Behavioral Control*
AVC: *Actual/Volitational Control*
HP: *Habitual Processes*

E: Matrix Code

B: *Benefits Matrix; all questions with this tag will be measuring benefits*
C: *Challenges Matrix; all questions with this tag will be measuring challenges (non-standard Likert [see numeric section])*
I: *Information Matrix; all questions with this tag ask about trusted information sources (non-standard Likert [see numeric section])*
M: *Management Matrix (BDST); all questions with this tag refer to aspects of biodiversity managed for*
P: *Practice Matrix (BDST); all questions with this tag refer to types of practices used in management of biodiversity*

R: *Results Matrix; all questions with this tag answer the question: "as a result of my project"*

N: Numbers

n: The number in succession of what the question is trying to measure

X: Text

X: Indicates there is text that tries to summarize what the question is about

.: Broadcast Operator

.: Indicates that the question has display logic attached to the previous question (with the same name)

In addition, I have attempted to standardize the numeric output of the survey. Here is a brief description of the numbers:

Likert Type Questions: 1-5

1 is always 'negative' 5 is always 'positive'

EXCEPT

when attached to a challenges matrix [see E section C from above] where 1 is no challenge and 5 is a great challenge (sort of reverse coded)

when attached to an information matrix [see E section I from above] where non-use of a source is 0, 1 is infrequent source, and 5 is frequent source

when the wording of the question asks importance, in which case 1 is not important and 5 is extremely important (sort of reverse coded)

Descriptive Questions: 1-n

Order of items listed in survey

Questions with a 'Unsure/Don't Remember (Know)' Option: -1

Indicates the above option was selected, unless option was 'not measuring economic outcomes'

Binary Optioned Questions: 0-1

Where 1 means yes

Appendix C. Reclassification Code for Analysis

Compatibility

```
##Read in libraries for dataframes and creating tables and
non-linear regression

using DataFrames, XLSX, StatsBase, GLM, Missings,
RegressionTables, StatsModels, CSV, ROCCurves


##Read in data from excel file

##Imputed

CCI = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "CCI"))

    for c ∈ names(CCI, Any)

        CCI[!, c]= Float64.(CCI[!, c])

    end

CPI = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "CPI"))

    for c ∈ names(CPI, Any)

        CPI[!, c]= Float64.(CPI[!, c])

    end

SMI = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "SMI"))

    for c ∈ names(SMI, Any)

        SMI[!, c]= Float64.(SMI[!, c])

    end

##Non-Imputed

CC = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "CC"))

    CC = coalesce.(CC, -99)

    for c ∈ names(CC, Any)

        CC[!, c]= Float64.(CC[!, c])

    end

    CC = ifelse.(CC .== -99, missing, CC)
```

```
CP = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "CP"))
    CP = coalesce.(CP, -99)
    for c ∈ names(CP, Any)
        CP[!, c]= Float64.(CP[!, c])
    end
    CP = ifelse.(CP .== -99, missing, CP)
SM = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
LASSO 2.xlsx", "SM"))
    SM = coalesce.(SM, -99)
    for c ∈ names(SM, Any)
        SM[!, c]= Float64.(SM[!, c])
    end
    SM = ifelse.(SM .== -99, missing, SM)
HSP = DataFrame(XLSX.readtable("/Users/jjtan/Downloads/HSP
Cleaned 5.14.xlsx", "Sheet1"))
    HSP = coalesce.(HSP, -99)
    for c ∈ names(HSP, Any)
        HSP[!, c]= Float64.(HSP[!, c])
    end
    HSP[!, c]=Float64.(HSP[!, c])
```

Appendix D. Sample Regression Code

```
##Cover Crop Models

    ##RAA

        ccraa = @formula(H_CC_Persist ~ RAA_A +  RAA_PBC +
RAA_AVC + RAA_N)

        ccraa_df = CC[:,
[:H_CC_Persist, :H_CC_Expand, :H_CC_RAA_IA_1, :H_CC_RAA_EA_
1, :H_CC_RAA_IN_1, :H_CC_RAA_DN_1, :H_CC_RAA_DN_2, :H_CC_RA
A_PBC_1, :H_CC_RAA_PBC_2,

            :H_CC_RAA_AVC_1, :H_CC_RAA_AVC_2, :H_CC_RAA_AVC
_3, :H_CC_RAA_AVC_4]]

        ccraa_df = dropmissing(ccraa_df,
disallowmissing=true)

            RAA_N = sum(eachcol(select(ccraa_df,
[:H_CC_RAA_IN_1, :H_CC_RAA_DN_1, :H_CC_RAA_DN_2])))

                ccraa_df[!, :RAA_N] .= RAA_N

                latent_m_ccr_n = Matrix(select(ccraa_df,
[:H_CC_RAA_IN_1, :H_CC_RAA_DN_1, :H_CC_RAA_DN_2]))

                CCRAA_N =
cronbachalpha(cov(latent_m_ccr_n))

            RAA_PBC = sum(eachcol(select(ccraa_df,
[:H_CC_RAA_PBC_1, :H_CC_RAA_PBC_2])))

                ccraa_df[!, :RAA_PBC] .= RAA_PBC

                latent_m_ccr_p = Matrix(select(ccraa_df,
[:H_CC_RAA_PBC_1, :H_CC_RAA_PBC_2]))

                CCRAA_P =
cronbachalpha(cov(latent_m_ccr_p))

            RAA_AVC = sum(eachcol(select(ccraa_df,
[:H_CC_RAA_AVC_1, :H_CC_RAA_AVC_2, :H_CC_RAA_AVC_3, :H_CC_R
AA_AVC_4])))

                ccraa_df[!, :RAA_AVC] .= RAA_AVC

                latent_m_ccr_v = Matrix(select(ccraa_df,
[:H_CC_RAA_AVC_1, :H_CC_RAA_AVC_2, :H_CC_RAA_AVC_3, :H_CC_R
AA_AVC_4]))
```

```
                CCRAA_V =
cronbachalpha(cov(latent_m_ccr_v))
            RAA_A = sum(eachcol(select(ccraa_df,
[:H_CC_RAA_IA_1, :H_CC_RAA_EA_1])))
                ccraa_df[!, :RAA_A] .= RAA_A
                latent_m_ccr_a = Matrix(select(ccraa_df,
[:H_CC_RAA_IA_1, :H_CC_RAA_EA_1]))
                CCRAA_A =
cronbachalpha(cov(latent_m_ccr_a))
        CCraa = glm(ccraa, ccraa_df, Binomial(),
LogitLink())
            aic(CCraa)
            deviance(CCraa)
            r2(CCraa, :McFadden)
```