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Testing Modified Sense of Place Measures on Working Landscapes in Iowa

by

Elizabeth Bennett

A thesis

submitted in partial fulfillment

of the requirements for the degree of

Master of Arts in the Department of Sociology, Social Work, and Criminology

Idaho State University

Summer 2021

To the Graduate Faculty:

The members of the committee appointed to examine the thesis of Elizabeth Bennett find it satisfactory and recommend that it be accepted.

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TABLE OF CONTENTS

List of Figures

List of Tables

Testing Modified Sense of Place Measure on Working Landscapes in Iowa

Thesis Abstract – Idaho State University (2021)

Sense of place (SOP) has been used on amenity landscapes to understand pro-environmental behavior. On working landscapes, SOP has not been a valid or reliable predictor of conservation behavior. In response to the troubles identified with SOP on working landscapes, Eaton et al. (2019) suggested several conceptual and measurement solutions. In this study, we test the modified SOP measures, along with the addition of scales of responsibility and good farmer identity, to explore the relationship between the multiple dimensions of SOP and conservation behavior. We used data from the 2017 Iowa Farm & Rural Life Poll and a Bayesian logistic regression. We show that physical dependence and economic dependence are distinct dimensions of SOP on working landscapes and find support for the addition of a scalar component. Our results suggest that SOP has the potential to be predictive of conservation behavior on working landscapes, but requires further reconceptualization and testing.

Keywords: Good farmer identity, economic dependence, agricultural land, cover crops

Introduction

Farm management practices can have significant negative impacts on the environment, including soil erosion and water quality impairment (Floress et al. 2018). In the United States, governmental and non-governmental efforts to address these impairments largely focus on incentivizing the voluntary adoption of conservation practices by individual farmers through cash payments, tax breaks, and other policy instruments (Ranjan et al. 2019). Because the adoption of conservation practices is voluntary, a large multi-disciplinary body of literature has examined the motivations, barriers, and other factors that influence farmer conservation decision-making in an effort to help design programs and policies to incentive conservation practice adoption. Despite this extensive research, two recent comprehensive reviews of the U.S. focused farmer conservation decision-making literature found that there have been few theoretical frameworks or individual factors that consistently predict or shape the adoption of conservation behaviors (Prokopy et al. 2019; Ranjan et al. 2019; also see Prokopy et al. 2008).

Theoretical frameworks and individual factors used in previous research on farmer conservation behavior have mostly used 1) rational actor models that assume behavior is guided by a self-interested attempt to make a decision that will maximize benefits and an assumption that others will do the same (Peterson & Isenhour 2014); or 2) individual level factors, such as farm size, education level, and income to predict farmer conservation behavior (Prokopy et al. 2019). However, farmer decisions cannot be explained as an attempt to maximize benefits or be predicted by individual level demographic variables and land use alone, and previously used theories and frameworks fail to adequately account for the complex interaction of scale, markets, institutions, identity, and policy that influence farmer behavior (Carlisle 2016; Reimer et al. 2014; Prokopy et al. 2019). Additionally, individual level factors do not capture the social, political, and economic context that decisions are made in or how these factors can be influenced by space, time, and institutions (Reimer et al. 2014). The inadequacy of these previously used theories and frameworks is demonstrated by researcher's inability to identify individual variables or conceptual frameworks that consistently predict conservation behavior.

Given the mixed-results of past efforts, researchers have turned to the literature on sense of place (SOP) —defined as the affective, cognitive and functional relationships and bonds people have with places (Eaton et al. 2019; Mullendore et al. 2015)—to provide new insights into what shapes the voluntary adoption of conservation practices by farmers in working landscapes, because individuals with high levels of SOP have been shown to engage in high levels of environmental concern and pro-environmental behavior in amenity landscapes (Cross et al. 2011; Eaton et al. 2018; Eaton et al. 2019; Mullendore et al. 2015; Brehm et al. 2013). Sense of place provides researchers with a tool to capture the complex relationships people have with landscapes. Rather than viewing farmers as actors on a landscape, SOP considers the multi-faceted relationship between farmers and the landscapes and how that relationship can influence conservation behavior.

However, the SOP concept was originally developed and used to explore the affective, cognitive, and attitudinal relationship between humans and the land in amenity landscapes—landscapes valued and used for the aesthetic and recreation opportunities the land provides (Brehm et al. 2004; Trentelman 2009; Gosnell & Abrams 2011)— and its application in working landscapes has met little success. In particular, researchers have struggled to 1) validly and reliably operationalize the SOP measures developed in amenity landscapes in working landscapes; and 2) provide evidence that traditional SOP measures have a clear relationship with conservation attitudes and behaviors (Eaton et al. 2019). This is perhaps not surprising given that farmers' relationships with and use of their land is distinctly different from the relationships people living in amenity landscapes have with their land (Eaton et al. 2019). Whereas amenity landscapes provide an opportunity for recreation and leisure, working landscapes provide the opportunity to produce commodity goods and are directly tied to livelihoods, meaning the relationships people have with them are likely functionally and affectively different than those people have with amenity landscapes (Plieninger et al. 2012; Eaton et al. 2019). To overcome the troubles researchers have encountered operationalizing the SOP concept in working landscapes, Eaton al. (2019) proposed a series of new survey items designed to better measure the emotional and cognitive bonds and functional dependencies farmers have with the land where they live and work than more amenity focused SOP measures. Our objective in this paper is to empirically test whether the solutions and new measures proposed in Eaton et al. (2019) better capture the multiple dimensions of SOP, and people-place relationships more broadly, in working landscapes and their relationship with conservation behavior than previous studies.

Previous adoption research has explored a number of conservation behaviors on working landscapes (Prokopy et al. 2019; Ranjan et al. 2019). In this study we focused on the adoption of cover crops in the working landscapes of Iowa because of their ability to effectively minimize soil and water degradation and associated issues due to monoculture, while not being considered a radical or transformative technology (Bergtold et al. 2012). Cover crops offset the impacts of corn and soy production by increasing organic matter in the soil, and crops with a tap root, such as tillage radish, minimize erosion and sediment in waterways by stabilizing the soil and have been promoted heavily in the Corn Belt as a method of reducing the soil and water degradation caused by extensive corn and soy monocultures (Roesch-McNally et al. 2017). Additionally, cover crops that fix nitrogen, such as alfalfa and winter rye, decrease the need for chemical fertilizers, lessening the harmful effects of farm runoff on watersheds (Clark 2007). Considering the potential benefits of cover crops to soil and water health, sense of place provides a framework to explore the adoption of cover crops in Iowa.

In the paragraphs below, we briefly describe several conceptual and measurement solutions developed by Eaton et al. (2019) to solve the troubles encountered measuring SOP in working landscapes and linking it to farmer conservation behavior. We then outline our data collection and analysis method. We conclude with our results and discussion and suggestions for future research.

Alternative measures of sense of place and related concepts

Below, we outline the measurement changes and additions Eaton et al. (2019) proposed to improve the reliability and validity of the SOP concept for use in working landscapes. We briefly review their proposed changes to modify the following existing SOP dimensions: 1) adding economic dependence to capture aspects of functional dependence not present in the place dependence concept; 2) better measurements of place dependence; and 3) the addition of the concept of scales of responsibility to incorporate the spatiality of social groups that a person identifies with and feels responsible to when making management decisions. Additionally, to incorporate the suggestion of Eaton et al. (2019) to measure conservation ethic along with SOP, we have included measurements of good farmer identity —which acknowledges how farmer identities are tied to broader social ideas of what constitutes a good farmer (McGuire et al. 2015) — to better account for the multiple types of identity that shape farmer conservation attitudes and behavior

Sense of place

Sense of place is typically conceptualized as being comprised of three sub-components: place identity, place attachment, and place dependence. Place identity describes how much a place and the associated physical environment is part of how a person sees themselves or wants others to see them (Eaton et al. 2019; Jorgensen & Stedman 2001; Williams & Vaske 2003). Place attachment is the positive affective bond between a person, or group, and a place (Amsden et al. 2011; Eaton et al. 2019; Jorgensen & Stedman 2001). Place dependence describes a functional relationship between an individual and place and reflects how well a place provides a person with the ability to achieve goals or desired outcomes, as compared to other locations (Eaton et al. 2019; Jorgensen & Stedman 2001). However, on working landscapes, place dependence and other SOP components have varied from these definitions.

Improving place dependence: economic dependence

Efforts to operationalize the SOP constituents described above on working landscapes has encountered several primary challenges. First, place dependence, as defined on amenity landscapes, was repeatedly shown to fail to capture the functional dependencies farmers have with working landscapes (Mullendore et al. 2015; Cross et al. 2011) that expand beyond the lifestyle dependence that SOP on amenity landscapes has measured. Functional dependence measures how the characteristics of a landscape allow a person to pursue their livelihood and economic intentions (Eaton et al. 2019). To encompass the unique functional relationship working lands actors have with their land, Eaton et al. (2019) suggest adding a measure of economic dependence to the place dependence construct to capture the multifunctionality of landscapes. Economic dependence on working landscapes has been difficult to capture in previous research, despite attempts to measure it across working landscapes and conservation behaviors. For example, in a study of the adoption of conservation easements by agricultural landowners in Wyoming and Colorado, a distinct economic dependence dimension was both a significant dimension of SOP and had a negative association with the adoption of conservation easements (Cross et al. 2011). In contrast, in the midwestern United States, economic dependence was found to not be a distinct component of SOP (Mullendore et al. 2015). The specific measures we used to measure economic dependence are described in our methods section.

Improving place dependence: physical dependence

Economic dependence does not capture the entirety of a farmer's functional dependence on working landscapes. Place dependence is a measurement of how well a physical landscape allows a person to achieve their goals and do what they do or enjoy most (Jorgensen & Stedman 2006). Previous studies have found that there is not a relationship between place dependence and conservation behavior (Eaton et al. 2019). However, this research has used measurements of place dependence focused on lifestyle dependence, rather than livelihood dependence, which does not effectively capture the intertwined role of livelihoods with lifestyles of farmers. Eaton et al. (2019) propose several measures that capture the unique physical dependence on working landscapes in which a landscape provides the most biophysical advantages for farmers to meet non-economic goals. The specific measures we used to measure place dependence are described in our methods section.

Improving place identity: scales of responsibility

To enhance conceptualization and measurement of place identity, Eaton et al. (2019) suggest adding a series of questions designed to measure the spatial and temporal components of place and connected social groups that a farmer identifies with and feels responsible to when making management decisions—what they call scales of responsibility. Previous research using SOP on working landscapes has only considered one scale (e.g., farm, community, or region) (Lewicka 2011; Eaton et al. 2019), with the majority of focus on the farm-scale (Reimer et al. 2014). This single-scale view fails to consider identity and associated behavior as it impacts and is impacted by larger scales of social-ecological organization and interactions with community and global policies and institutions, thus failing to capture the multifunctional and multi-scalar aspects of farms and farming, as well as how individual farmer identities are embedded in and shaped by wider social contexts and the collective identities of other agricultural producers and consumers (Naylor et al. 2018). However, doing so is important because the decisions and behavior of farmers on working landscapes are connected to a broad suite of larger social, economic, environmental contexts, ranging from family traditions to international policy and markets to global circulation of carbon dioxide (Reimer et al. 2014; Prokopy et al. 2008). Likewise, farmers grow and provide food to not only themselves and their local community but to people and markets that span not only their states and countries but also the globe. Accordingly, farmer identity and behavior are impacted by who they feel responsible to and believe will benefit from their actions (e.g., their own land or families, people who live in or the environment of their watershed, state, or the entire world), as well as the social groups that individuals identify with and the scale at which those groups operate (Eaton et al., 2019; Wilson et al., 2018). The specific measures we used to measure scales of responsibility are described in our methods section.

Improving place identity: good farmer identity

In addition to scales of responsibility, we incorporated the concept of good farmer identity into our measurement and analysis of SOP to better account for the multiple types of identity that shape farmer conservation attitudes and behavior, as well as to broadly capture our respondent's conservation ethic. A conservation ethic is defined as a person's sense of responsibility for managing land in ways that improve the well-being of people and the environment (Eaton et al. 2019). While SOP provides a potential framework to understand farmer adoption of conservation behavior, its narrow conceptualization of identify fails to consider how farmers perceive their role in society and how their ideas about what makes a person a good farmer lead to particular management orientations focused either on maximizing production or protecting the environment, both of which have been shown to be important components of farmer identities (Burton 2004; Arubuckle 2013; Sulemana & James 2014). In particular, farmer identities are tied to broader social ideas of what constitutes a good farmer, and farmers both want to self-identify as and be identified by others as good farmers (McGuire et al. 2015). Typically, farmers conceptualize what makes a good farmer in two ways. The first is a productivist good farmer, one who is focused on maximizing yield, profit, and the short-term health of the land. In contrast, conservationist good farmers are focused on environmental stewardship and the long-term health of the land (McGuire et al. 2013; McGuire et al. 2015). While two types of good farmers have been identified, there is not a clear dichotomy between them. Rather, farmers exist on a good farmer continuum as they attempt to balance the aesthetics and economic benefits of their farmland and their stewardship behavior (McGuire et al. 2013; Burton, 2004). Nonetheless, the good farmer concept has been used in research on conservation behavior of farmers and has been shown to be predictive of the adoption of a wide range of conservation behaviors (McGuire et al. 2015; Burton & Wilson 2006, McGuire et al. 2013). We describe the specific measures used to measure good farmer identity in our methods section.

Methods

Study site

The data we use in this study were collected in the midwestern US state of Iowa. Iowa and the broader upper-Midwest are known for fertile soils that support large-scale corn and soy production (Arbuckle et al 2013; Roesch-McNalley et al. 2017). Eighty four percent of the terrestrial land base in Iowa is classified as agricultural by the United States Department of Agriculture, and the agricultural industry in Iowa employs 216,700 people (NASS 2017). Additionally, Iowa produces over half of the corn and soy in the US (NASS 2017; NASS 2009, 2011). However, soy and corn growing practices contribute to soil erosion through the removal of organic material, erosion due to tilling practices, leaching of soil nutrients, especially nitrogen (King et al. 2016; NRCS 2007), and creation of nitrogen and phosphorus rich runoff that is detrimental to watershed health. For example, hypoxia in the Gulf of Mexico has been linked to fertilizer and pesticides in runoff flowing from Iowa (Jones et al. 2018; Roesch-McNalley et al. 2017). In addition, Iowa has experienced recent changes in weather patterns and extreme weather events driven by climate change that compound the negative environmental effects of soil and corn production on soil health (Arbuckle et al. 2013). As such, cover crop adoption is considered an important practice to lessen the negative effects of agriculture on the environment, specifically the effects of corn and soy production Iowa.

Survey and response rate

To answer our research objective, we used data from the 2017 Iowa Farm and Rural Life Poll (IFRLP). The IFRLP is a longitudinal panel survey that has been conducted every other year since 1982 by the Iowa State University Sociology Extension program. The survey is distributed by Iowa Agricultural Statistics using a modified Tailored Design Method (Dillman et al. 2014) that follows survey-postcard-survey mailing protocol. The 2017 sample was composed of 2,250 farmers who could potentially earn $1,000 or more in agricultural income from their land, and survey recipients may or may not be active farmers. Of these, 170 surveys were returned to us because recipients no longer farmed, were deceased or retired, or were otherwise ineligible, leaving us with an eligible sample of 2,080. In total, we received 999 usable surveys for a 48% response rate. However, due to cover crops being most effective on corn and soy fields, we did not include surveys from farmers who did not grow corn or soy. After removing surveys from farmers who did not grow corn or soy and item level non-response, the analysis we present here is based on 726 cases.

The IFRLP contains questions about quality of life, farm and financial well-being, soil and water conservation practices, and socio-demographics. In 2017, in addition to the typically asked questions, we included a series of questions taken from Eaton et al.'s (2019) modified SOP measures and their scales of responsibility concept. Additionally, in 2017, the IFRLP included questions designed to measure good farmer identity.

To assess non-response bias, we compared our respondent profiles to the target population across several farm characteristics using data from the 2017 Census of Agriculture. The comparison shows that the IFRLP sample has a slight bias towards older farmers, likely due to the longitudinal survey method used (Arbuckle 2013), and is slightly biased towards larger farmers and farmers with greater sales (see Table 1).

Table 1: Comparison of Iowa Farm and Rural Life Poll (IFRLP) respondents and USDA Census of Agriculture

	IFRLP	Census of Agriculture
Average farm size	432	355 acres
Farms with less than $10,000 in farm sales	17%	38%
Farms with sales greater than $50,000	63%	48%

Variable measurement and modeling approach

In our results section below, we present results from a Bayesian logistic regression model to assess how SOP, good farmer identity, and scales of responsibility influence farmer adoption of cover crops. Answering our research objective required two stages of data analysis. First, because there were high correlations between many of the individual, observed variables within each of our constructs of interest, which indicates that our data is not one dimensional, we used confirmatory factor analysis on each of our question sets to measure the hypothesized latent dimensions underlying our data (Brown & Moore 2012). Confirmatory factor analysis provides a method to test hypothesized latent variables that underlie a set of individual survey items designed to measure a conceptual construct by identifying measures that covary, which indicates that they are influenced by the same underling construct (Brown & Moore 2012). We based the number of factors chosen for each confirmatory analysis on Eaton et al.'s (2019) review of SOP on working landscapes and previous literature on good farmer identity (Arbuckle 2013; Roesch-McNally et al. 2017). We used the p*sych* package in R to conduct our confirmatory factor analysis. We used a promax rotation because it allows for high correlation among individual items and maximizes dispersion, meaning a small number of observed variables load strongly on each factor (Brown 2009). To measure the internal consistency of each identified factor, we used Chronbach's alpha. Factors with a Chronbach's alpha >.70 are considered to be sufficiently reliable (Nunnally 1978). Following the confirmatory factor analysis, we computed Bartlett factor scores to determine the location of each surveyed individual on the factor. Bartlett's approach is preferable to other scoring approaches because it provides an unbiased estimate of factor scores (DiStefano et al. 2009). Before describing the second stage of data analysis, we describe how our predictor and outcome variables were measured and generated. As part of this, we present the results of our factor analysis here rather than in our results section, because the generated factors are predictor variables in our model.

Sense of place

To measure SOP, we asked respondents to indicate their level of agreement with 15 statements taken from Eaton et al. (2019) designed to measure place identity, place attachment, and place dependence in working landscapes. Each question used Likert-scale response options, which ranged from 1 = strongly disagree to 4 = strongly agree. We hypothesized that the SOP survey items would factor into three latent variables corresponding to the concepts of place attachment, place dependence and place identity. Our factor analysis identified three distinct types of SOP, though they did not correspond perfectly to our hypothesized factors. We named the first factor place attachment and identity (Cronbach's alpha=.90). We named the second factor physical dependence (Cronbach's alpha = .90). We named the third factor community (Cronbach's alpha = .90). We present the results of our factor analyses and associated survey items in Table 2.

Table 2. Description of survey items measuring sense of place [a]

	Rotated factor loadings[b,c]		
Item description	**Attachment & Identity**	**Dependence**	**Community**
When I think of home, I think of the land I farm	.53		
I feel happiest when I am on the land I farm	.53		
The land I farm is my favorite place to be	.55		
The land I farm is an important part of who I am			
My personal history is closely tied to the land I farm			
Even if I were no longer farming, the land I farm will always be a part of who I am			
It is important to me that the land I farm stay in my family			
The friendships I have developed through farming activities in the area where I farm are important to me			
Farmers in the area where I farm generally have beliefs and values similar to mine			.50
I have a trusted network of people I talk with about farming in the area where I farm			.50
There aren't many job opportunities available to me other than farming			
The land I farm is important to my economic well-being			
The characteristics of the land I farm (soil type, topography, etc.) are largely responsible for my success as a farmer			
If I could farm anywhere in the world, it would be the land I farm now		.50	
Even though there might be better places to farm, I would rather farm in the area where I farm than anywhere else		.61	
I would feel out of place farming anywhere else			
Cronbach's alpha	.90	.90	.90
Eigenvalue	3.63	2.23	1.69

[a] Item scale: 1=strongly disagree, 2=somewhat disagree, 3=somewhat agree, 4=strongly agree
[b] Oblique promax rotation
[c] Blanks represent rotated factor loadings < 0.5

Scales of responsibility

To measure scales of responsibility, we asked respondents to indicate their level of agreement with eight statements designed to measure the scale that a farmer considers when making management decisions. Each question used Likert-scale response options, which ranged from 1 = not at all responsible to 4 = very responsible. We hypothesized that the scales of responsibility survey items would factor into three latent variables corresponding to the concepts of an individual scale of responsibility, a watershed scale of responsibility, and a global scale of responsibility. Our factor analysis identified three distinct scales of responsibility that corresponded to our hypothesized latent variables. We named the first factor on-farm (Cronbach's alpha=.90). We named the second factor watershed (Cronbach's alpha = .89). We named the third factor global (Cronbach's alpha = .90). Our scales of responsibility factor analysis results and associated survey items are presented in Table 3.

Table 3. Description of survey items measuring scale of responsibility [a]

Item description	Rotated factor loadings[b,c]		
	On-farm	**Watershed**	**Global**
Previous generations of my family			
Myself	.54		
My immediate family	.60		
My neighbors		.50	
People in the area where I farm		.54	
People in my watershed			
Everyone on planet earth			.55
Future generations			.60
Cronbach's alpha	.90	.89	.90
Eigenvalue	2.3	1.5	1.38

[a] Item scale: 1=not at all responsible, 2=somewhat responsible, 3= moderately responsible, 4=very responsible
[b] Oblique promax rotation
[c] Blanks represent rotated factor loadings < 0.5

Good farmer identity

To measure good farmer identity, we asked respondents to indicate their level of agreement with 15 statements taken from the good farmer literature (McGuire et al. 2013; McGuire et al. 2015). Each question used Likert-scale response options, which ranged from 1 = not important at all to 5 = very important. We hypothesized that the good farmer identity items from the IFRLP would factor into two latent variables corresponding to the concepts of productivist identity and conservationist identity (Arbuckle 2013). Our factor analysis identified two distinct types of good farmer identity. We named the first factor conservationist (Cronbach's alpha=.85). We named the second factor productivist (Cronbach's alpha = .86). Our good farmer identity factor analysis results and associated survey items are presented in Table 4.

Table 4. Description of survey items measuring good farmer identity [a]

Item description	Conservationist	Productivist
A good farmer is one who has the highest yields per acre		.61
A good farmer is one who minimizes soil erosion	.62	
A good farmer is one who gets their crops planted first		.59
A good farmer is one who considers the health of streams that run through or along their land to be their responsibility	.72	
A good farmer is one who increases overall profitability by identifying and improving management of unprofitable subfield areas		
A good farmer is one who minimizes nutrient runoff into waterways	.74	
A good farmer is one who has the highest profit per acre		.56
A good farmer is one who maintains or increases soil organic matter	.61	
A good farmer is one who uses the latest seed and chemical technology		.60
A good farmer is one who has the most up-to-date equipment		.64
A good farmer is one who puts long-term conservation of farm resources before short-term profits	.63	
A good farmer is one who maximizes government payments		
A good farmer is one who minimizes tillage		
A good farmer is one who scouts before spraying for pests/weeds/disease	.55	
A good farmer is one who thinks beyond their own farm to the social and ecological health of their watershed		
Cronbach's alpha	.85	.86
Eigenvalue	4.22	2.72

[a] Item scale: 1=strongly disagree, 2=somewhat disagree, 3=somewhat agree, 4=strongly agree

[b] Oblique promax rotation

[c] Blanks represent rotated factor loadings < 0.5

Economic dependence

Because economic dependence did not load onto our derived factors, we included it in our model as a standalone variable to enable us to test hypothesis 4 in Table 6. To measure economic dependence, we asked respondents to rate their agreement, 1 = strongly disagree to 4 = strongly agree, with the following statement: the land I farm is important to my economic wellbeing.

Control variables

To account for the influence of variation in sociodemographic, land ownership, and land use characteristics on our response variable, we included several control variables based on findings from previous literature (Prokopy 2019). The variables were age, income from farming, type of crops grown, whether or not respondents produced livestock, and whether or not respondents rented farmland. Descriptive statistics for our control variables are displayed in Table 5 below.

Table 5. Descriptive statistics of control variables. Binary and categorical variable are reported as percent of respondents in each category

Age (years)	18 – 54 years old	13.9%
	55 – 64 years old	32.6%
	65 – 74 years old	33.3%
	75 + years old	18.6%
Crop type (Binary)	Row	Yes (69%)
	Specialty	Yes (72%)
	Diversified	Yes (87%)
Income	$0 - $49,999	30.2%
	$50,000 - $149,999	31.7%
	$150,000 – $349,999	20.5%
	More than $349,999	13.4%
Livestock producer (binary)		Yes (29%)
Rent farmland (binary)		Yes (49%)

Outcome variable

Our outcome variable for the Bayesian logistic regression model was a binary measure of cover crop adoption. To measure this, we asked respondents to indicate if they had (1) used a practice in 2017; (2) Not used it in 2017 or had no plans to use it; or (3) Not used in 2017 but might use it in the future. We gave the dependent variable a value of one if a respondent indicated they had grown cover crops in 2017. It was given a value of zero if a respondent indicated they had not grown cover crops 2017 and had no plans to in the future or they had not grown cover crops in 2017 and might use them in the future. The relationships we hypothesized between latent and other predictor variables and our outcome variable are displayed in Table 6.

Table 6: Hypothesized relationships between latent variable and cover crop adoption

	Variable	Relationship to cover crop adoption	Citations
	Sense of place		
1)	Place attachment & identity	Positive	Ulrich-Schad et al. (2015); Cross et al. (2011)
2)	Physical lace dependence	Negative	Mullendore et al. (2015); Eaton et al. (2019)
3)	Community	No relationship	
4)	**Economic Dependence**	Negative	Cross et al. (2011)
	Scales of responsibility		
5)	On-farm	Negative	Eaton et al. (2018)
6)	Watershed	Positive	Eaton et al. (2018)
7)	Global	Positive	Eaton et al. (2018)
	Good farmer identity		
8)	Conservationist	Positive	Roesch-McNally et al. (2018)
9)	Productivist	Negative	Roesch-McNally et al (2018)

Statistical modeling

Bayesian Logistic Regression

Following the factor analysis, the relationship between the identified latent variables and cover crop adoption was analyzed using a Bayesian logistic regression model. We used a Bayesian logistic regression with Markov Chain Monte Carlo (MCMC) sampling to estimate the influence of our SOP, good farmer, and scales of responsibility latent variables, as well as economic dependence, on cover crop adoption. The model was fit using the R package *rstanarm* (Goodrich et al. 2020), and we chose to use the weakly informed default priors of (0, 2.5), which is a conservative, but flexible approach that allows for exploratory analysis (Lemoine 2019; Fraser et al. 2010).

Model fit

To evaluate model fit, we analyzed trace plots for convergence of MCMC chains. Trace plots convergence indicates that a stationary distribution has been met and the chains have converged around mean values. Trace plots can be assessed for convergence visually. Trace plots that have converged will show multiple chains scattering around a mean value, or mixing (Jackman 2009). All trace plots in our study indicated that the MCMC chains had converged. In addition, we assessed Rhat values as an additional measure of convergence (Vehtari et al. 2019). A Rhat value of 1 is considered good and a value of 1.1 or greater indicates that chains did not mix well. All Rhat values for observed and latent variables were 1.0. We assessed goodness of fit of the binary logistic regression model by evaluating the area under the receiver-operating curve (AUC) (Robin et al. 2011). AUC is a model fit measurement that indicates how well a model is at distinguishing between classes or outcomes. The higher an AUC value, the better a model is a distinguishing between classes (Zipkin et al. 2012). In this study, the classes the model is distinguishing between are whether a farmer adopted cover crops or not. An AUC > 0.75 is regarded as a good model fit as this indicates that 75% of the time a model will predict an outcome correctly (Williamson et al. 2020). However, this heuristic was derived from medical literature in which distinguishing between classes requires a higher level of precision than in the social sciences. Our model had an AUC of .70, which indicates that 70% of the time our model will accurately predict whether or not a farmer adopted cover crops.

Strength of association of individual predictors

To assess the strength of evidence that a predictor in our model was strongly associated with cover crop adoption, we calculated the proportion of the posterior probability distribution that exceeded zero for each of the model's predictor variables. When > 0.90 or < 0.10 of the posterior predictive mass for the regression coefficient ≥ 0, we judged that predictor as strongly positively or strongly negatively associated with the response variable, respectively. Because we used relatively uninformative priors, posterior proportions > 0.9 equate to odds ratios of > 10, which are evidence of strong positive associations, and posterior proportions < 0.10 are equal to odds ratios of < 0.10, which are indicative of strong negative associations (Jeffreys 1961; Williamson et al. 2020). Further, rather than interpreting the strength of association between predictors and the response variable by comparing the magnitudes of the regression coefficients, we provide marginal effects plots that show how our outcome variable changes as a function of a change in the value of a single predictor variable.

Results

Of the 726 respondents that answered the question asking them to indicate if they grow or planned to grow cover crops, 21% reported having adopted cover crops. Table 7 presents the Bayesian logistic regression results and model fit statistics.

Table 7. Bayesian logistic regression results and model fit statistics

Variable	Mean (SD)	%> 90	%>10
Intercept	-1.2 (0.4)	0.09	99.93
Attachment & Identity	0.3 (0.3)	86.8	13.45
Physical Dependence	-0.3 (0.3)	13.1	86.95
Community	0.0 (0.3)	48.13	51.88
On-farm	0.2 (0.2)	77.03	22.99
Watershed	-0.4 (0.2)	2.78	97.23
Global	0.5 (0.2)	98.73	1.28
Productivist	-0.2 (0.2)	5.60	94.40
Conservationist	0.4 (0.2)	99.40	.60
Economic Dependence	0.0 (0.1)	73.08	26.93

Sense of place & cover crop adoption

We hypothesized a positive association between attachment and identity and cover crop adoption. We found support for a potentially strong but uncertain positive association between attachment and identity and cover crop adoption. Figure 1a illustrates the association between place attachment and place identity scores and farmer's adoption of cover crops. Our hypothesized negative association between physical dependence and cover crop adoption was supported with a potentially strong but uncertain negative association. As shown in Figure 1b, as dependence scores increase the probability of a farmer adopting cover crops decreases. Finally, we hypothesized a positive association between community and cover crop adoption. We did not find an association between community and cover crop adoption. This is shown in Figure 1c.

Scales of responsibility & cover crop adoption.

As we hypothesized, we found that on-farm had a strong but uncertain positive association with cover crops and global scales of responsibility had a strong positive association with cover crop adoption. In contrast to our hypothesis, we found that a sense of responsibility to local watersheds had a strong negative association with the adoption of cover crops. Figure 1d, 1e, and 1f illustrate these relationships.

Good farmer identity & cover crop adoption

We hypothesized a negative association between productivist farmer identity and cover crop adoption and a positive association between conservationist farmer identity and cover crop adoption. Both of these hypotheses were supported with a strong negative association between productivist farmer identity and the probability of a farmer adopting cover crops and a strong positive association between conservationist farmer identity and the adoption of cover crops. These relationships are illustrated in Figure 1g and 1h.

Economic dependence & cover crop adoption

We expected that farmers who indicated they were more economically dependent on farming would be less likely to grow cover crops. However, we found a strong but uncertain positive association between economic dependence and cover crop adoption. Figure 1i illustrates the association between economic dependence scores and farmer's adoption of cover crops.

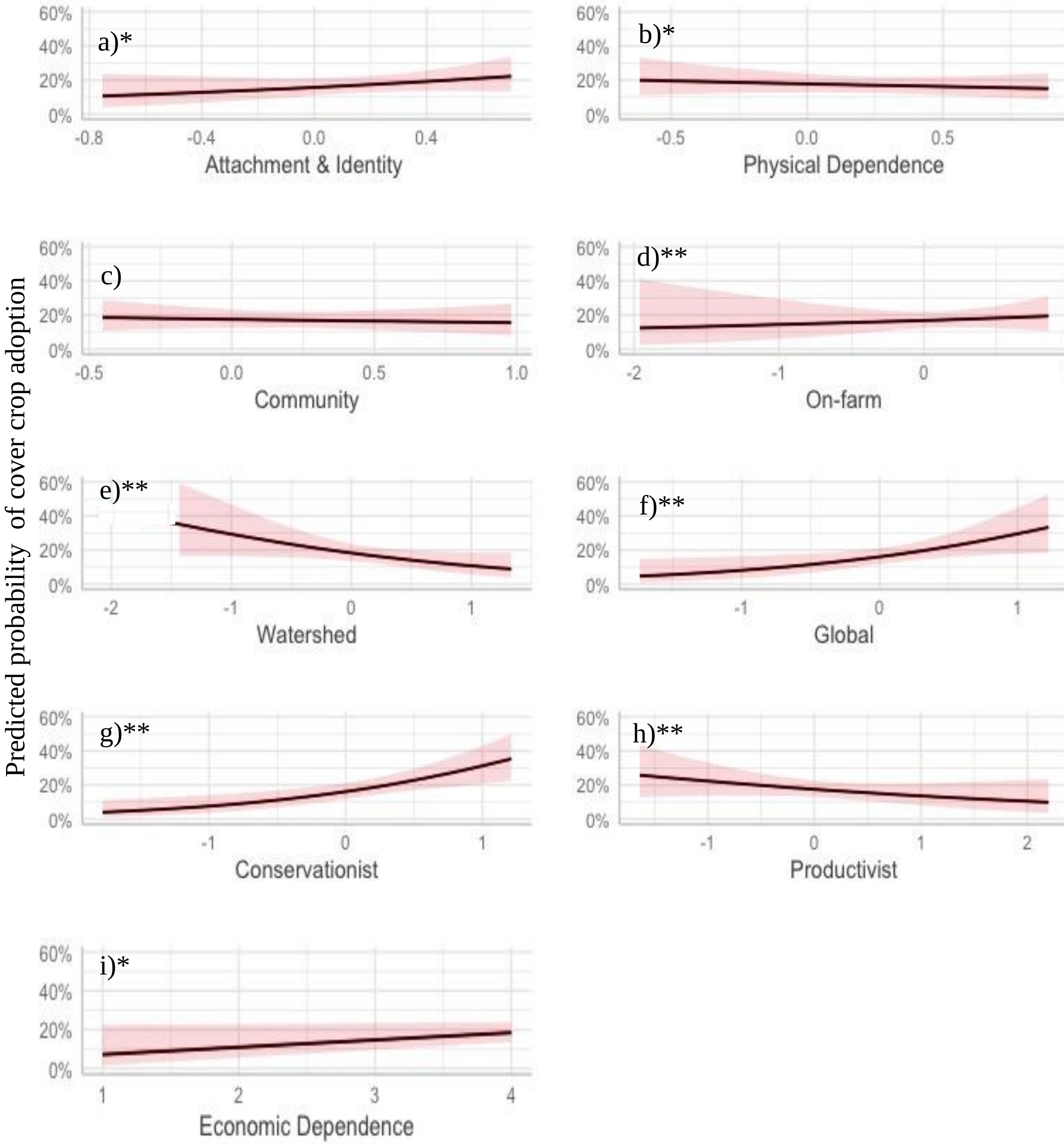

Figure 1. Predicted probability of cover crop adoption for each predictor variable. *= strong relationship. ** = strong but uncertain relationship.

Discussion

Overall, our results seem to validate Eaton et al.'s (2019) call for the development and use of SOP measures tailored to working landscapes, while also suggesting that continued refinement of the measures is needed to validly and reliably measure SOP on working landscapes. In the following discussion, we highlight findings that speak to how well these new and reconceptualized dimensions of SOP on working landscapes worked and where there is room for improvement.

Economic dependence

In our study, we found two distinct types of place dependence amongst our respondents: economic and physical dependence. Both had strong but potentially uncertain relationships with cover crop adoption. In particular, in the factor analysis, our measure of economic dependence did not factor in with our other measures of place dependence, supporting the findings of Cross et al. (2011) and Mullendore et al. (2015) that together suggest that economic dependence is a unique dimension of SOP on working landscapes. Furthermore, we found that economic dependence was positively (but uncertainly) associated with cover crop adoption. Economic dependence has been a particularly troublesome SOP dimension to define and measure. In a study of Colorado and Wyoming agricultural landowners Cross et al. (2011) found that higher levels of economic dependence were negatively associated with the adoption of conservation easements. In their study of midwestern farmers, Mullendore et al. (2015) found that economic dependence was not a distinct component of SOP and nor was it encompassed within physical dependence. It also had no association with farmer adoption of various conservation behaviors, including conservation tillage and grassed waterways. Further lending to these inconsistent findings, we found that in contrast to our hypothesized negative association, economic dependence was positively associated with the adoption of cover crops.

We suggest that the discrepancies in the relationship between economic dependence and conservation behavior in each of the three studies that have tested it may be the outcome of the different conservation behaviors each explored, and future research should examine the role of economic dependence in conservation adoption across a wide range of conservation behaviors. Further, while strongly positive, there was a fair amount of uncertainty in the relationship between our economic dependence measure and cover crop adoption**,** which suggests that more research is needed to better understand the role of economic dependence in the adoption of conservation behavior on working landscapes. In particular, a broader conceptualization of economic dependence is likely needed. Following Bastian et al. (2020), we suggest that future research should include both financial and non-financial economic benefits derived from landscapes, including income, wealth generation, and amenity rents. For example, grazing permits are a valuable wealth generation tool on working landscapes, but do not explicitly provide income (Bastian et al. 2020). Additionally, the satisfaction landowners receive from owning land, managing their land, and providing environmental benefits can be captured by the concept of landowner amenity rents (Bastian et al. 2020). Bastian et al. (2020) suggest that landowner amenity rents should be included as part of economic dependence, rather than physical dependence, because they often provide financial and non-financial economic benefits to the landowner and community. We agree with the suggestion as our results do not indicate that physical dependence includes landowner amenity rents.

Overall, our results support the idea that economic dependence should be included as a standalone dimension of SOP on working landscapes in future studies. We echo Eaton et al.

(2019) and Bastian et al.’s (2020) suggestion for a broader and more valid conceptualization of economic dependence. While economic dependence in our study was measured by a single survey item measuring dependence on the income provided by farming, we propose future studies the addition of economic benefits to economic dependence to capture the complexity of the benefits that working landscapes provide to working landscape actors.

Physical dependence

In addition to economic dependence, our factor analysis revealed a separate physical dependence dimension in our study. Physical dependence measures how a physical landscape allows a person to achieve their goals and do what they enjoy most (Jorgensen & Stedman 2001). We found a strong (but uncertain) negative relationship between our physical dependence factor, which was constructed to capture the multiple forms of functional dependence of farmers on place, and the adoption of cover crops. This finding differs from recent research that showed that physical dependence has no association with conservation behavior in working landscapes (Eaton et al. 2019). We suggest that the difference is that we used questions designed to capture the non-economic functional dependence of farmers on their land that were specific to farming, whereas past studies asked broader questions about dependence on land taken from studies focused on recreation in amenity landscapes. Similar to Eaton et al. (2019), we found that items related to livelihood, rather than lifestyle, (e.g., “If I could farm anywhere right now, it would be the land I farm”) factored into a distinct physical dependence dimension of SOP. This supports Eaton et al.’s (2019) suggestion that physical dependence on working landscapes includes both a livelihood and lifestyle component, rather than just the typical lifestyle component used in research in amenity landscapes. Further, our results suggest that on working landscapes standalone SOP dimension of physical dependence should be used alongside measures of economic dependence.

Scales of responsibility

Following the suggestion of Eaton et al. (2019), we included a scalar component in our study to capture the spatial and temporal components of place that a farmer feels responsible to when making management decisions. Our factor analysis identified three distinct scales of responsibility.

On-farm

In our factor analysis, we identified an on-farm scale of responsibility in which farmers were concerned for their own well-being and health of their land. We found that an on-farm scale of responsibility had a strong but uncertain positive association with the adoption of cover crops, which contrasts previous research that found a negative relationship between a person having a strong sense of responsibility to their farm and conservation behavior. In their study of bioenergy crop adoption, Eaton et al. (2018) found that farmers who believed their land should only be used to benefit themselves were less likely to adopt bioenergy crops. We suggest that the difference may have resulted from the conservation practice of interest in each study. Planting bioenergy crops in the northeast United States is largely done to mitigate climate change and offers low return on investment, thus making their use largely directed at solving global challenges. While cover crops mitigate regional and broader scale water quality problems, they also have more on-farm benefits than bioenergy crops. As such, the different findings between the two studies are likely determined by interactions between the scalar benefits of the conservation practice investigated and the scales of responsibility reported by respondents. The inconsistency of an on-farm scale of responsibility in predicting conservation behavior suggests that more research is needed to understand the relationship between an on-farm scale of responsibility and conservation behavior, and especially how it influences conservation behavior across different management practices.

Watershed

In our factor analysis, we identified a watershed scale of responsibility that we hypothesized would have a positive association with the adoption of cover crops. However, we found that a watershed scale of responsibility was strongly negatively associated with the adoption of cover crops. Previous research has shown that a watershed scale of responsibility can be negatively associated with conservation practices when farmers have concerns about the environmental and community impacts of a practice (Eaton et al. 2018). Additionally, farm management policies can constrain conservation or motivate behavior at a watershed level. In Iowa, conservation districts at that watershed scale provide information and guidance to farmers regarding farm management practices, such as the adoption of cover crops, and their guidance likely influences what conservation behavior farmers do and do not adopt (Reimer 2014; Cross et al. 2011). Often, the guidance provided regarding farm management is shaped by input by local farmers, which points to the potential importance of social networks in shaping watershed scales of responsibility and associated conservation behavior (IDALS 2021; Prokopy 2015). We suggest that more research is needed to better understand the impacts of a watershed scale of responsibility and the other potential drivers of conservation behavior at a watershed scale. Following previous research, we suggest that future studies include measures of attitudes about conservation behaviors and consider the role of local and regional policies in influencing conservation behavior at a watershed scale (Reimer 2014).

Global

Our factor analysis identified a global scale of responsibility in which farmers were concerned about both the global population and future generations. Consistent with previous research (Eaton et al. 2018), we found that farmers with higher global scale of responsibility factor scores were strongly and positively more likely to adopt a conservation practice. Unlike previous studies that analyzed the role of scales of responsibility in shaping conservation behavior, our measures included a temporal component of concern for future generations. We suggest that the reason our temporal responsibility measure factored with the global measure of responsibility may be due to concerns about family farm succession (Inwood & Sharp 2012). As agriculture faces increased stressors from changing climatic conditions and social pressures, adapting and adopting conservation practices is becoming imperative to maintain farmland for future generations. Additionally, a concern for the future of the agricultural economy could contribute to these findings (Inwood et al. 2013). As with farm succession, current farming practices are likely not sustainable and the adoption of conservation practices provides one way to support the future of agriculture.

Overall, our results indicate that Eaton et al.'s (2019) suggestion of adding a scalar component to SOP research on working landscapes is valuable. In our study, all three scales of responsibility were at least fairly strongly associated with the adoption of cover crops. We suggest that future SOP studies include scales of responsibility and consider both the spatial and temporal scale that farmers consider when making management decisions.

Good farmer identity

Consistent with previous research (Roesch-McNally et al., 2018), our factor analysis identified conservationist and productivist farmer identities that were both strongly predictive of conservation behavior. In particular, and as expected, we found a strong positive association between conservationist farmers and the adoption of cover crops. This finding is consistent with previous research on good farmer identity that found a positive relationship between conservationist identity and conservation behavior (Burton 2004; Arubuckle 2013; Sulemana & James, 2014). Likewise, as expected, we found a strong negative relationship between productivist farmer identity and cover crop adoption. The negative relationship we found is consistent with previous studies that have examined how good farmer identity affects conservation practice adoption (McGuire et al. 2015). While these results are unsurprising, they suggest that good farmer identity should be included as an additional measure in future SOP studies to expand its conceptualization of identity beyond the traditional SOP definition of how a person wants to be or sees themselves as part of the landscape to include how a person's identity is connected to how they believe a landscape should look and be managed. Additionally, while our findings suggest that good farmer identity is strongly associated with conservation behavior, we did not test how good farmer identity interacts with individual SOP components. Due to the strong association between good farmer identity and the adoption of cover crops we suggest that additional research is needed to understand how good farmer identity potentially interacts with other SOP dimensions to influence both conservation behavior and other SOP components.

Attachment & identity

We found that unlike on amenity landscapes, attachment and identity did not factor into two separate SOP dimensions. Rather, consistent with other research on working landscapes (Ulrich-Schad et al., 2015; Cross et al., 2011), we found that attachment and identity were closely related and varied together to comprise one attachment/identity factor that was strongly (but uncertainly) positively associated with the adoption of cover crops. This finding supports the suggestion of Eaton et al. (2019) to reconceptualize SOP on working lands. In this case, we suggest that on working landscapes attachment and identity together may comprise one standalone SOP dimension. We suggest that this is due to the attachment a person feels to their landscape and the role of the landscape in how they want to be seen and are seen by others are closely related. In addition, Cross et al. (2011) found that in a study of agriculturalists in Colorado and Wyoming, place attachment/identity variables aligned with their conservation ethic scale. This suggests that the attachment identity variable could be also measuring some aspects of conservation ethic. In our study, we did not explicitly measure conservation ethic. However, more research is needed across working landscapes and conservation behaviors to identify if attachment and identity consistently comprise one variable and continue to be predictive of conservation behavior, as well as to identify the relationship between attachment and identity and a conservation ethic.

Community

Our factor analysis produced a unique variable, community, that has not been identified in previous research. Based on the survey items that factored into community, we suggest that that the community factor could be a measure of social networks (Prokopy et al. 2019). Previous research on the conservation behavior of farmers has found that social networks can be associated with the adoption of cover crops (Prokopy et al. 2019). However, it is not clear if community is measuring a social network dimension of SOP. Additionally, in this study, community did not have a relationship with the adoption of cover crops. Considering this, we suggest more research on SOP on working landscapes to identify if a community factor consistently occurs on working landscapes and has a relationship with conservation behavior.

Conclusion

Farm management practices significantly contribute to soil erosion and water quality degradation. To encourage the voluntary adoption of practices that minimize the negative environmental impacts of farm management practices, governmental and nongovernmental incentives have been used. However, despite incentives, the adoption of conservation practices has been difficult to predict. Because of this, researchers have turned to SOP as a framework to better understand what motivates farmer conservation behavior. Using a Bayesian logistic regression, we tested updated measures of SOP specific to working landscapes to test whether these new measures of SOP were predictive of farmer's adoption of cover crops in Iowa. We found that a number of modified SOP dimensions were predictive of cover crop adoption. Additionally, we found that the value of SOP might be enhanced when paired with additional concepts. As our results show, scales of responsibility and good farmer identity were both predictive of the adoption of cover crops and indicate that additional concepts that have been predictive in previous research can be meaningful additions to SOP research on working landscapes. We suggest that future research continue to test the modified measures of SOP with an emphasis on applying the modified measures across conservation practices and landscapes.

Finally, our study has several limitations. First, other factors not included in our study could contribute to the adoption of cover crops, including the influence of rented farmland compared to owned farmland because whether someone rents or owns the land they farm on may influence their SOP. While we were able to identify if a farmer rented farmland or not, we were unable to capture the influence of landowners, especially corporate ownership, on decision making on rented farmland. Additionally, the role of ISU Extension Service and the Iowa Department of Agriculture and Land Stewardship in distributing the IFRLP could limit our results as farmers connected with the IFRLP could be more involved with extension services than other farmers, suggesting that they would be more likely to receive information on conservation behaviors, such as cover crops. In turn, this may mean that a higher proportion of our sample adopted cover crops than we would have found if the survey was disseminated in another way.

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