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Bivariate MIMIC Analysis of Pasture Management and Prescribed Grazing Practices Used by Beef Cattle Producers

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This study applies a bivariate multiple indicator–multiple causation model to examine farm and operator characteristics associated with the likelihood of using pasture management (PM) and prescribed grazing (PGR) practices. Data are from a survey of cattle operations. Most commonly used practices included adjusting livestock and pasture fertilization. Least used were geotextiles in trafficked areas and buffering sensitive areas. Use of PM practices was income-sensitive. Land stewardship and government conservation incentive views influenced PGR. Results suggest complementarities between most PGR and PM practices. However, those with higher opportunity costs and off-farm benefits (e.g., stream crossings) are not complementary with other practices.

Key words: bivariate MIMIC, pasture management, prescribed grazing, U.S. cattle producers

Introduction

The use of best management practices (BMPs) for livestock grazing and pasture management can mitigate the environmental impacts of livestock production by reducing nutrient runoff, soil erosion, and greenhouse gas emissions while also improving forage quality and animal productivity (U.S. Department of Agriculture, 2010a; Briske et al., 2011; Sollenberger et al., 2011; Conant et al., 2017). In some instances, BMPs increase the profitability of an agricultural operation and are readily adopted by producers (Hopkins and Johansson, 2004). In other circumstances, the financial incentives provided by federal and state agencies are critical to motivate the voluntary adoption of conservation practices (Claassen, Duquette, and Smith, 2018).

Research on the use and voluntary adoption of BMPs is extensive (e.g., Knowler and Bradshaw, 2007; Prokopy et al., 2008; Baumgart-Getz, Prokopy, and Floress, 2012; Pannell, Llewellyn, and Corbeels, 2014; Liu, Bruins, and Heberling, 2018). A subset of studies focuses on the adoption and use of pasture management BMPs by livestock producers (e.g., Kim, Gillespie, and Paudel, 2005, 2008; Gillespie, Kim, and Paudel, 2007; Lambert et al., 2014a; Jensen et al., 2015). In general, these studies focus on the adoption of single practices or technologies, explicitly or implicitly assuming that the adoption decision is independent of both previous adoption decisions and current or future opportunities to adopt other practices or technologies (Dorfman, 1996; Khanna, 2001; Kassie et al., 2013; Kpadonou et al., 2017; Lambrecht, Vanlauwe, and Maertens, 2016; Fleming, 2017; Liu, Bruins, and Heberling, 2018; Ward et al., 2018). However, perceived or quantifiable interactions between practices may significantly influence a producer's decision to adopt one or

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Table 1. Pasture Management and Prescribed Grazing Practices Included in Survey Questions to Beef Cattle Farmers

Pasture Management Practices	Prescribed Grazing Practices
Applying manure as fertilizer to pastures (U.S. Department of Agriculture, 2013b)	Balanced livestock consumption and forage production
Applying N, P, or K fertilizer (DAP, urea, LAN, etc.) to pastures (U.S. Department of Agriculture, 2013b)	Adjust numbers, fertilizer rates, or purchase feed to meet forage needs
Controlling livestock access to streams (U.S. Department of Agriculture, 2008)	Limit feed (grain etc.) to $\leq 50\%$
Having improved stream crossings (U.S. Department of Agriculture, 2011b)	Pasture weed control plan
Watering cattle at site other than a stream or pond (U.S. Department of Agriculture, 2010c)	Use ≥ 5 different grazing paddocks
Having buffer strips of woody or grassy vegetation along waterways (U.S. Department of Agriculture, 2008, 2010b)	Graze ≤ 14 continuous days on paddock
Protecting heavy use areas with geotextiles (U.S. Department of Agriculture, 2010a)	Buffered sensitive areas
Having shade structures, scratching posts, and feed supplements placed away from streams(U.S. Department of Agriculture, 2013a)	Developed or followed a conservation plan w/grazing component
Replanting bare pasture with legumes or native grasses (U.S. Department of Agriculture, 2011a), and	Grazed $\leq 20\%$ of pasture to less than min. grazing heights
Periodically testing soil (U.S. Department of Agriculture, 2013b)	

more technologies (Lambrecht, Vanlauwe, and Maertens, 2016). For example, pairs or bundles of BMPs could exhibit increasing returns to scale in terms of on-site profitability and on- or off-site environmental outcomes. As a result, the adoption or availability of one practice could increase expectations about on-site benefits and, therefore, the likelihood of the adoption of other BMPs (Dorfman, 1996; Fleming, 2017; Griffin et al., 2017; Khanna, 2001; Liu, Bruins, and Heberling, 2018). In other situations, producers may perceive BMPs as substitutes, such that the use of one practice diminishes the likelihood of, or even precludes, the adoption of other practices. Thus, substitute and complementary relationships among BMPs have implications for the design of educational outreach and incentive programs intended to encourage BMP adoption as well as the measurement of the on- and off-site economic and environmental outcomes associated with BMP adoption.

This research uses data from a survey representative of beef cattle operations east of the 100th meridian to examine the association between cattle producer and farm business attributes and the adoption of 10 pasture management (PM) and nine prescribed grazing (PGR) practices (Table 1). A bivariate multiple indicator–multiple causation (MIMIC) model is used to estimate the propensity of producers to use these practices as linear functions of operator attributes, farm characteristics, and farmer attitudes. The bivariate MIMIC approach controls for the effects of unobserved interaction components between technologies perceived by producers as latent variables—and the effect of these interactions on adoption—holding operator and farm business attributes constant.

The MIMIC framework reduces the problem dimension of estimating the association between farm and producer factors and the adoption of 19 discrete grazing management practices. From a methodological vantage, modeling the propensity to adopt technology sets as correlated latent variables provides an alterntive approach toward understanding how producers perceive complementarities between practices as well as a parsimonious approach for modeling correlated, multivariate outcomes. From a practical standpoint, agency programs may group certain practices based on "common-sense" pragmatism but also perhaps for lowering the administrative costs of managing multiple contracts. Still, producers may group practices according to different criteria, such as personal experience, existing infrastructure (e.g., fence or pump lines), or profitability. The MIMIC model is therefore an alternative empirical approach for gauging the likelihood that producers would adopt or use practice bundles in contrast to, or in accordance with, formal programmatic definitions of practice systems.[1] For this study, analyzing PGR practices as a bundle is particularly appealing given that they comprise a system eligible for cost-share payments by the U.S. Department of Agriculture (USDA).

Background

The USDA's Natural Resources Conservation Service (NRCS) defines prescribed grazing as "the controlled harvest of vegetation with grazing animals" (NRCS Practice Code 528). Specific PGR practices include planned "intensity, frequency, timing and duration of grazing"; supplemental feeding, balanced with forage, to ensure desired nutritional levels of cattle; and the provision of shelter (U.S. Department of Agriculture, 2010b) (Table 1). Eligible producers may receive financial assistance to offset establishment and/or continued management costs for PGR under the USDA's Environmental Quality Incentives Program (EQIP). Off-site benefits of PGR include carbon sequestration, improved water infiltration by soils, reduced streambank erosion, and decreased manure loading into water systems. Another element of the PGR program is the establishment and management of riparian buffers, which help prevent streambank erosion and absorb nutrients like nitrogen and phosphorous before they enter waterways. The controlled grazing component also requires monitoring of grazing heights and grazing uniformity to minimize overgrazing. The rotational grazing component of PGR facilitates intensive but intermittent grazing in paddocks, providing time for forage pasture to recuperate. Producers document their activities and record minimum grazing heights for various grasses to qualify for cost-share assistance (U.S. Department of Agriculture, 2010a).

The EQIP program also provides cost sharing for a number of other grazing-related BMPs (Table 1). These PM practices can improve forage quality, maintain pasture soil health, reduce water quality degradation, safeguard livestock and animals against disease (Kemp et al., 2005), and improve farm aesthetics. However, unlike the PGR practices, the EQIP program considers these technologies as stand-alone practices.

Several studies have examined farmer adoption of BMPs on livestock operations and factors influencing this adoption. Winkle and Hadrich's (2011) analysis focused on two BMPs for North Dakota cattle producers: nutrient management and rotational grazing. They found that producers with relatively more education and those that managed larger operations and kept records were more likely to adopt rotational grazing. Ghazalian, Larue, and West (2009) studied the adoption of riparian buffer zones among crop and livestock producers in Quebec, Canada. They found that farmers with larger animal operations were more likely to install riparian buffers. Producer age, education, participation in agri-environmental clubs, and the operation's revenue from cattle sales and physical size were all positively associated with the probability of adopting riparian buffers. These studies provide important insights about producer and farm operation attributes associated with pasture BMP practice adoption, but they do not examine how farmer perceptions of complementary relationships between these practices influence their use as part of an overall PM or PGR program.

Gillespie, Kim, and Paudel (2007) studied the adoption patterns of Louisiana cattle operations for a larger group of best pasture and herd practices, including heavy-use protection areas, grassed waterways, livestock exclusion areas, riparian buffers, streambank and shoreline protection, watering facilities, rotational grazing, prescribed grazing, and nutrient management. The most

[1] See, for example, Czajkowski et al.'s (2017) treatment of consumer preferences as a system of latent variables.

commonly adopted practices were watering facilities, prescribed grazing, fencing, mortality management, and pesticide management, each of which was adopted by at least 60% of respondents. The least commonly adopted practices were those associated with environmental benefits, including water regulating systems, riparian buffers, cover and green manure crops, grass-lined waterways, and streambank and shoreline protection. None of these practices had been adopted by more than one-quarter of the producers.

Gillespie, Kim, and Paudel (2007) also used a multinomial logit model to correlate practice use with farm and farmer characteristics. They found a variety of farmer demographic and farm characteristics including age, education, interaction with Extension, planned family takeover, household income, percentage of income from beef, number of other crops, risk-aversion attitudes, and land attributes significantly influenced one or more practices used. Their findings provide important information regarding the effects of farm characteristics and farmer demographics on a range of BMPs. However, their study was limited to Louisiana beef producers and did not specifically consider correlations or groupings among practices.

Kim, Gillespie, and Paudel (2005) analyzed BMP use, both individually and in five predefined bundles, among Louisiana cattle producers. The five practice bundles were (i) livestock exclusion and fencing; (ii) riparian forest buffer, critical area planting, and livestock exclusion; (iii) water facility and heavy use area protection; (iv) critical area planting, livestock exclusion, and fencing; (v) and rotational grazing system with water facility and fencing. The most commonly adopted bundle was the rotational grazing system with water facility and fencing, at 35%, followed by the water facility and heavy use area protection bundle at 26%. The least commonly adopted bundle was the riparian forest buffer, critical area planting, and livestock exclusion bundle at 9%. Independent bivariate probit regressions were used to analyze the effects of farm and farmer characteristics on bundle use.

Lambert et al. (2014a) examined the willingness of cattle producers in southeast Tennessee to adopt different combinations of four BMPs—rotational grazing, water tanks, pasture improvement, and stream crossing. They found that the most commonly adopted combination was rotational grazing, cattle water tanks, and pasture improvement, followed by rotational grazing and pasture improvement. The least popular combinations were those including a stream crossing.

A better understanding of interactions among BMPs is critical for the design of effective educational and incentive programs htheir adoption (Feather and Amacher, 1994). For example, voluntary incentive programs promoting the adoption of one BMP can also have indirect effects on the adoption of other BMPs. Fleming (2017) found that a cost-share incentive for cover crop adoption in Maryland increased not only the use of cover crops but also the use of conservation tillage. Thus, an estimate of the environmental and other benefits of the incentive program that failed to recognize the secondary effects of the incentive on conservation tillage use would underestimate these benefits. This type of effect has been termed "crowding in," as the public investment, in the form of adoption incentives, engenders increased private investment from agricultural producers. At the other end of the spectrum, Lambert et al. (2014a) found a substitute relationship between rotational grazing and stream crossings for cattle producers whose pasture included or bordered a stream. Thus, an incentive program that attempted to induce producers to adopt these practices as a bundle could prove ineffective. Other studies also find indirect effects of adoption incentives on adoption of other BMPs (e.g., Dorfman, 1996; Amacher and Feather, 1997; Wu and Babcock, 1998; Khanna, 2001; Cooper, 2003) or synergistic/complementary relationships in BMP use (e.g., Lichtenberg, 2004; Watcharaanantapong et al., 2014; Lambert, Paudel, and Larson, 2015; Ward et al., 2016; Griffin et al., 2017; Ulrich-Schad et al., 2017).

Bivariate MIMIC Adoption Model

The MIMIC structure is well suited for modeling the use of multiple, discrete technologies as a function of latent variables. Latent variables measure the producer's propensity to use one or a set of technologies. Skrondal and Rabe-Hesketh (2004) describe MIMIC regressions as multifactor latent variable models that facilitate the simultaneous estimation of factors associated with discrete variables in a general linear framework. A typical MIMIC model consists of (i) a measurement model defining the relationships between a latent variable and its indicators and (ii) a structural model specifying the effects of causal variables on the latent variable. In this research, the propensity to use one or several technologies is modeled as a single latent variable, conditioned on the causal factors. Numerous studies have employed MIMIC models to analyze aggregate technical efficiency and change in agriculture (e.g., Gao, 1994; Gao and Reynolds, 1994; Kalaitzandonakes and Monson, 1994; Esposti and Pierani, 2000; Richards and Jeffrey, 2000) and technology adoption (e.g., Maddala, 1983; Kalaitzandonakes and Monson, 1994; Lambert, Paudel, and Larson, 2015; Sok et al., 2015; Borges, Tauer, and Lansink, 2016; Morais, Binotto, and Borges, 2017). MIMIC formulations of technology adoption typically use a single latent variable to model the adoption of a suite of practices. This study formulates a bivariate MIMIC adoption model by introducing two latent variables that explain simultaneously the propensity to use two technology bundles—PM and PGR practices. Our approach allows arbitrary correlation between the errors of the latent use propensity scores.

The bivariate MIMIC model estimates the propensity to adopt PM and PGR practices as evidenced by the use of two sets of practices ("indicators") (Table 1). The latent propensity scores associated with each bundle are determined by a set of explanatory ("causal") variables, including farmer demographic variables, farm operation attributes, and regional variables.[2] Given that the NRCS treats PGR as an integrated system requiring adoption of one or more individual BMPs, we consider the PGR practices as a separate group of indicators from other PM practices. Unobserved factors between practice bundles, such as perceived complementariness, may be correlated with the producer's decision to adopt other practices. We therefore allow arbitrary correlation between the error terms of the "propensity to adopt" latent variables. This treatment also reflects the structure of the survey used to collect the data (described below), which had separate sections for PM and PGR.

Structural Equations

Consider technology sets p (PGR practices) and m (PM practices). A producer may adopt PGR practice p_j to optimize forage production (Table 1). These structures and management practices are generally oriented toward controlling the movement of livestock on pasture to allow forage to regenerate, sustain higher stocking densities, and increase the availability of high-quality forage (U.S. Department of Agriculture, 2010d). As a result, these practices are likely complementary, enhancing effectiveness when used together. Producers may also adopt PM practice m_k to repair, establish, or maintain pasture productivity (Table 1). These practices are oriented toward maintaining pasture productivity through fertilization, replanting bare areas, and minimizing soil erosion by controlling animal access to water sources.

Producer i uses one or a combination of discrete technologies belonging to set p or m. The propensity to use individual technologies from either set may be correlated because of unobserved variables associated with dissonant or complementary technologies. The propensity to use PGR or PM practices is a system of linear index functions:

$$(1) \qquad \begin{bmatrix}\boldsymbol{\eta}_i^p\\ \boldsymbol{\eta}_i^m\end{bmatrix} = \begin{bmatrix}\boldsymbol{Z}_i & 0\\ 0 & \boldsymbol{Z}_i\end{bmatrix}\begin{bmatrix}\boldsymbol{\Gamma}^p\\ \boldsymbol{\Gamma}^m\end{bmatrix} + \begin{bmatrix}\boldsymbol{\zeta}_i^p\\ \boldsymbol{\zeta}_i^m\end{bmatrix},$$

where $(\boldsymbol{\eta}_i^p, \boldsymbol{\eta}_i^m)$ are latent variables (adoption propensities); $\boldsymbol{Z}_i$ is a $g \times 1$ vector including operator demographic and farm business and structural variables (Table 2); $(\boldsymbol{\Gamma}^p, \boldsymbol{\Gamma}^m)$ are conformable vectors

[2] Climate, landscape, and other environmental factors likely influence BMP use. However, NASS prepared the sample and conducted the mailings, so the only location information available to the authors was that of ERS region (U.S. Department of Agriculture, Economic Research Service, 2000). Regional dummy variables reflecting ERS region are included in the model to capture regional variation in rainfall, temperature, and terrain.

Table 2. Variable Names, Definitions, and Means Used in Modeling Pasture Management and Prescribed Grazing Practices Adoption by Beef Cattle Farmers

Variable Name	Description	(N = 716)
Pasture management practices (PASTMAN) and prescribed grazing practices (PGR) indicators		
WATER	1 if water cattle at site other than a stream or pond; else 0	0.711
BUFF	1 if buffer strips of woody/grassy vegetation along waterways; else 0	0.437
SHADE	1 if shade struct., scratch. posts, feed sup. away from streams; else 0	0.694
CROSS	1 if have improved stream crossings; else 0	0.247
ACCESS	1 if control livestk. access to streams; else 0	0.286
GEOTEX	1 if protect heavy use areas with geotext.; else 0	0.126
REPLANT	1 if replant bare pasture with legumes or native grasses; else 0	0.550
SOILTEST	1 if periodically test soil; else 0	0.662
MANURE	1 if apply manure as fert. to pastures; else 0	0.451
NPK	1 if apply N, P, or K fert. (DAP, urea, LAN, etc.) to pastures; else 0	0.612
Prescribed grazing practices (PGR) indicator variables		
BALANCE	1 if balance livestock consumption and forage production, else 0	0.598
ADJUST	1 if adjust livestk. numb., fert. rates, purch. feed for forage, else 0	0.740
LIMIT	1 if limit feed (hay, silage, glut., hulls, grain etc.) $\leq$ 50% of diet, else 0	0.471
WEED	1 if use a pasture weed control plan, else 0	0.627
PADD	1 if used at least 5 different paddocks or fields for grazing, else 0	0.571
GRAZL	1 if graze livestk. $\leq$ 14 continuous days on any paddock/field, else 0	0.304
BUFFS	1 if buffer sensitive paddock areas (wells, sinkholes, etc.), else 0	0.215
CONSP	1 if develop/followed conserve. plan incl. grazing component, else 0	0.257
GRZHT	1 if graze $\leq$ 20% of pasture to less than min. grazing hghts., else 0	0.339
Explanatory variables		
AGE	Operator age in years	60.605
COLLEGE	1 if attended college; else 0	0.682
MEETING	No. Extension meetings or workshops attended in 2012	1.219
INTERNET	1 if use Internet to make purchases or management decisions	0.543
PASSON	1 if operator plans to pass farm on to family; else 0	0.635
WAIT	1 if "wait and see" attitude for technology adoption; else 0	2.725
GOV	1 if believe govt. should provide incent. for conserve. pract.; else 0	3.693
STEWARD	1 if believe farmers are stewards of land; else 0	4.763
*INCLT*30	1 if income<$30K; else 0	0.091
*INC*3049	1 if $30K–$49.9K; else 0	0.170
*INC*5099	1 if $50K–$99.9K; else 0	0.433
SHRBEEF	Percentage of farm income from cattle operation	40.557
OFF-FARM	Labor hours/week off-farm	0.318
ACRES	Acres farmed, in 100-acre increments	6.818
SHRPAST	Share of farmland in pasture	0.538
STKRATE	Stocking rate (in animal-unit-month)	0.495
HEART	1 if located in Heartland region; else 0	0.222
PRAIR	1 if located in Prairie Gateway region; else 0	0.180
EAST	1 if located in Eastern Uplands region; else 0	0.268
SOCO	1 if located in Southern Coastal region; else 0	0.168
NORTH	1 if located in Northern region; else 0	0.099
MISS	Mississippi Portal is the omitted base region	0.061

of coefficients; and $(\boldsymbol{\zeta_i^p}, \boldsymbol{\zeta_i^m})$ are error terms with expected values, correlation (ρ), and variances of

$$\text{(2)} \qquad \begin{bmatrix} \zeta_i^p \\ \zeta_{ji}^m \end{bmatrix} \sim BVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right).$$

The variances in equation (2) are normalized to 1 to identify the latent variable component of the bivariate MIMIC model (Maddala, 1983; Skrondal and Rabe-Hesketh, 2004). The (0, 1) technology indicators are regressed on the latent variables using the equation system

$$\text{(3)} \qquad \begin{bmatrix} p_{1i}^* \\ \vdots \\ p_{Ji}^* \\ m_{1i}^* \\ \vdots \\ m_{Ki}^* \end{bmatrix} = \begin{bmatrix} \alpha_{10}^p \\ \vdots \\ \alpha_{J0}^p \\ \alpha_{10}^m \\ \vdots \\ \alpha_{K0}^m \end{bmatrix} + \begin{bmatrix} \lambda_1^p & 0 \\ \vdots & \vdots \\ \lambda_J^p & 0 \\ 0 & \lambda_1^m \\ \vdots & \vdots \\ 0 & \lambda_K^m \end{bmatrix} \begin{bmatrix} \eta_i^p \\ \eta_i^m \end{bmatrix} + \begin{bmatrix} \varepsilon_{1i}^p \\ \vdots \\ \varepsilon_{Ji}^p \\ \varepsilon_{1i}^m \\ \vdots \\ \varepsilon_{Ki}^m \end{bmatrix},$$

where $(\alpha_{j0}^p, \alpha_{k0}^m)$ are constants, $(\lambda_j^p, \lambda_k^m)$ are factor loadings, and the expected values of the $(\varepsilon_{ji}^p, \varepsilon_{ki}^m)$ are 0. The factor loadings correlate the propensity to use PGR or PM practices with the kth or jth technology, respectively. The indicator functions (p^*, m^*) are modeled using the logistic distribution, which means the error variances of the indicator functions are restricted as $\text{Var}(\varepsilon_{ji}^p) = \text{Var}(\varepsilon_{ki}^m) = \frac{1}{3}\pi^2$, with $\text{Cov}(\varepsilon_{ki}^m, \varepsilon_{ji}^p) = 0$ for identification. The variance–covariance restrictions are the usual assumptions maintained when performing multinomial logistic regression.[3] Cross-equation covariances are mediated through (i) the parameter ρ in equation (2), and (ii) through the (λ_j, λ_k) factor loadings (Maddala, 1983; Skrondal and Rabe-Hesketh, 2004; Lambert, Paudel, and Larson, 2015). The bivariate MIMIC model is estimated with STATA's generalized structural equation-modeling procedure (*gsem*) (StataCorp, 2015).[4] The *gsem* procedure is a structural equation-modeling system that allows for observed and latent variables with multilevel generalized outcomes and response types (e.g., binary or ordered) (Rabe-Hesketh and Skrondal, 2012). The procedure maximizes a pseudo-likelihood function with respect to the parameters.

Marginal Effects

Marginal effects measure the influence a unit, or discrete, change in operator and farm business attributes has on the probability of using technologies in the PGR or PM bundles. For example, the marginal effect of attribute Z_{ki} on the probability of using the jth PGR practice $\Pr(p_{ji}^* = 1)$ is

$$\text{(4)} \qquad \frac{\partial \Pr\left(p_{ji}^* = 1\right)}{\partial Z_{ki}} = \lambda_j^p \times f_\Lambda(\alpha_{j0}^p + \lambda_j^p \eta_i^p) \times \gamma_k,$$

where f_Λ is the probability density function of the logistic distribution and λ_j^p is the factor loading on the propensity to use PGR practices. Similar terms hold for use of technologies belonging to the PM set of practices. Standard errors of the marginal effects are calculated using the delta method (Greene, 2012).

[3] The usual assumptions are that the error terms of equation (3) are *i.i.d.* random variables with an expected value of 0 and a constant variance. As with most other regression estimators, the MIMIC estimator may produce biased or inconsistent estimates if these assumptions about the variance structure fail, if the covariates are correlated with unobserved factors in the error terms in equation (3), or if the factor error terms in equation (2) are generated from a distribution other than the multivariate normal.

[4] Program code is available from the authors on request.

Ex Post Cluster Analysis of Adoption Bundles

To confirm bundling, the predicted probabilities from the MIMIC model for each PM or PGR practice are analyzed using principle components analysis (PCA), which orders technologies according to the probabilities estimated from the logit regressions of equation (3). The use probabilities are therefore conditioned on the farm demographic variables. The number of principle components to include in the analysis was the number needed for the cumulative value of the eigenvalues to explain 98% of the variation of the probability vectors. Bundles were identified by inspecting the factor-loading plots of the first two principle components.

Data

The data are from a survey of beef cattle, cow/calf, and backgrounding/stocking operations from the eight Economic Research Service (ERS) regions east of the 100th meridian (Oliver, 2015). These regions (e.g., Heartland, Northern Crescent, Northern Great Plains, Prairie Gateway, Eastern Uplands, Southern Seaboard, Fruitful Rim, and the Mississippi Portal) are based on commodity production, geographical specialization, and other characteristics (Heimlich, 2000). A map of the regions is available from the authors. The USDA National Agricultural Statistics Service (NASS) conducted the mail survey in 2013. NASS randomly selected 8,875 operations from the population of beef cattle operations. The response rate was 26%.

Eight ERS regions and eight sales classes were used to post-stratify farms. Sales class categories used by NASS were farms with sales less than \$100,000, \$100,000–\$250,000, \$250,000–\$500,000, \$500,000–\$1,000,000, and greater than \$1,000,000. Post-stratification weights were calculated based on these strata using a raking procedure (Lambert et al., 2014b). The survey included questions about respondent's current use (in 2012) of the PM and PGR practices described in Table 1 and characteristics of the producer and beef cattle operation. After eliminating records with missing values, 716 observations were used to estimate the MIMIC model. The survey is available from the authors upon request.

More than 50% of the respondents used waterers, shaded areas for animals away from streams, replanted bare areas with native grasses or legumes, applied nitrogen–phosphorus–potassium (NPK) fertilizer, and periodically tested pasture soil (Table 2). The least used PM practices were protecting heavy use areas with geotextile (13%) and installing stream crossings (25%). Of the PGR practices, more than 50% of the respondents used paddocks, had weed control plans, balanced livestock consumption and forage production, and adjusted animal access to pasture to meet livestock forage needs.

Beef cattle operators more frequently used PM than PGR practices (Figure 1, left side). Visual inspection of the adoption frequencies of practices in both BMP sets suggests those that were correlated (Figure 1, right side). The MIMIC model examines these aggregated patterns conditioned on operator attributes and farm business characteristics.

Operator and Farm Characteristics

Literature on BMP adoption provides guidance on the factors likely to influence the use of PGR or best PM practices. The association between operator age (*AGE*) on BMP adoption varies, depending on the crop or livestock operation. Some BMPs may take several years to generate a positive net return. Limited-resource, retired, or part-time farmers are therefore less likely to adopt these conservation practices (Soule, Tegene, and Wiebe, 2000). Baumgart-Getz, Prokopy, and Floress (2012) also concluded that age was negatively correlated with adoption. Older producers may be less likely to alter production methods by incorporating BMPs if they do not perceive positive economic impacts (Lambert et al., 2006). However, age is positively correlated with the adoption of herbicide-

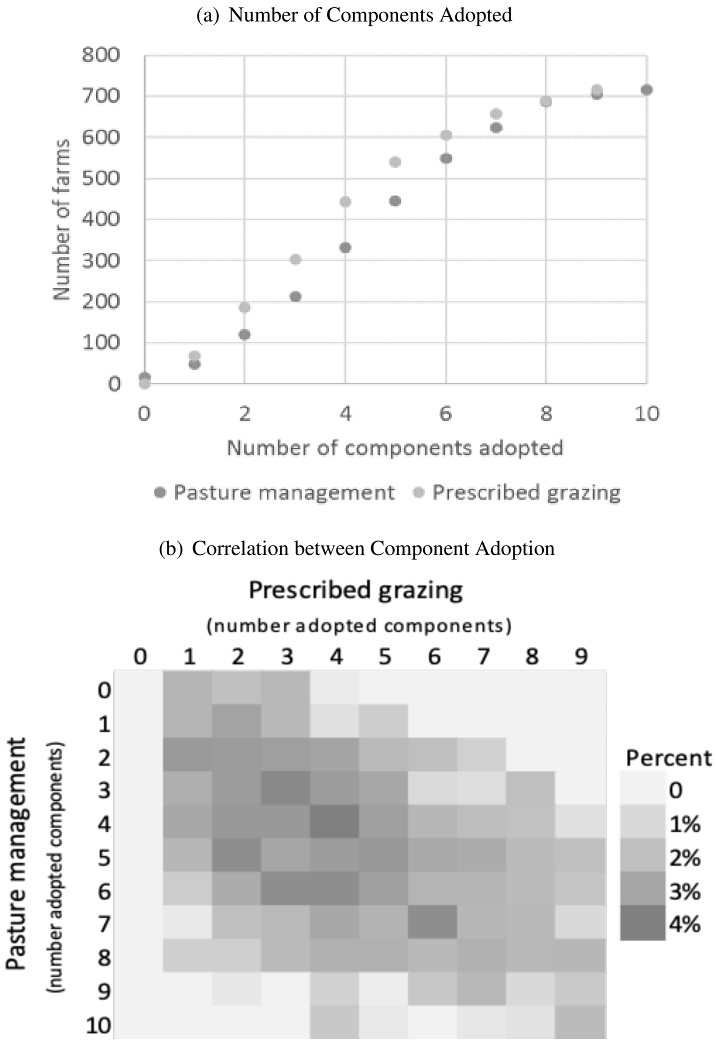

Figure 1. Number of Pasture Management and Prescribed Grazing Components Adopted and Correlation between Component Adoption by Beef Cattle Farmers

resistant seed technology among soybean producers (Fernandez-Cornejo, Hendricks, and Mishra, 2005) and with BMP adoption among beef cattle producers (Kim, Gillespie, and Paudel, 2005).

Education is positively correlated with BMP adoption (e.g., Daberkow and McBride, 1998; Soule, Tegene, and Wiebe, 2000; Fernandez-Cornejo, Hendricks, and Mishra, 2005; Gillespie, Kim, and Paudel, 2005, 2007; Kim, Gillespie, and Paudel, 2005). A dummy variable indicating whether the respondent had a college degree (COLLEGE) is included in the latent variable regressions.

The number, type, and quality of information sources producers use to learn about agricultural technologies influence the decision to invest in new practices or equipment (Jenkins et al., 2011). Given that producers may use the Internet to collect information about new technologies before adoption, the use propensity equations (equation 2) include a dummy variable indicating whether a respondent used the Internet to make farm purchase or management decisions (*INTERNET*).

Producers may also seek Extension services for information on integrating new practices into their operation. A number of studies find a positive correlation between adoption and use of Extension services (e.g., Greiner, Patterson, and Miller, 2009; Walton et al., 2010; Nair et al., 2011). For example, Gillespie, Kim, and Paudel (2005) found that producers working with Extension three or more times per year were more likely to adopt PGR practices, fencing, and watering tank systems. The number of extension meetings a respondent attended (*MEETING*) is included in the use propensity equations.

A dummy variable indicating respondent plans to bequeath the farm to children or kin (*PASSON*) is included in the latent variable regression. Respondents who expected their family to take over their farm may be more inclined to use practices that sustain pasture and forage productivity (Lambert et al., 2014a). However, as Shaikh, Sun, and Kooten (2007) found, producers may be unwilling to limit land use opportunities of the next generation.

Respondent beliefs that farmers are stewards of the land serves as a proxy for their attitude toward environmental stewardship and hence may be positively associated with the adoption of grazing-related BMPs. Likewise, producers amenable to assistance from state or federal conservation agencies may be more likely to adopt PGR and PM practices. The dummy variables *STEWARD* and *GOV* are included in the linear index model to control for these sentiments.

Producer risk preferences may also affect the propensity to adopt BMPs. Greiner, Patterson, and Miller (2009) found that producers who considered themselves less risk averse than other producers were more likely to adjust stocking rates and experiment with rotational grazing. Similarly, Gillespie, Kim, and Paudel (2007) found that risk-averse beef cattle producers were less likely to adopt BMPs than other beef cattle operations. Respondent self-reported proclivity to wait until others adopted technologies before adopting similar technologies themselves (*WAIT*) is included in the latent use equations to proxy attitudes toward risk.

Analyses of the relationship between household income and BMP adoption often distinguish between on- and off-farm income. Fernandez-Cornejo, Hendricks, and Mishra (2005) found a significant relationship between the adoption of herbicide resistant soybean varieties and off-farm income. Lambert et al. (2006) concluded that producers who do not supplement farm income with earnings from off-farm work were more likely to adopt conservation practices that increase farm receipts. Gillespie, Kim, and Paudel (2007) found no relationship between farm income earned from beef cattle and BMP adoption but a positive association between household income and the adoption of rotational grazing and fencing. Three dummy variables are included to control for the effects of income on the propensity to use PGR or PM practices. The dummy variables identified respondents who reported less than $30,000 in annual income from farming (*INCLT*30), $30,000–$49,000 (*INC*3049), $50,000–$99,000 (*INC*5099), and greater than $99,000 (the reference group). Operators earning a relatively larger share of their farm income from beef cattle production (*SHRBEEF*) may be more likely to adopt practices they perceive will enhance forage and livestock productivity and profit. Yet there are opportunity costs associated with the time invested to manage a beef cattle operation. The number of hours per week worked off farm (*OFF-FARM*) is included in the latent variable equations to control for the effects of off-farm employment opportunities on the propensity to use PGR and PM practices.

Previous studies are mixed with respect to the effect of farm size on BMP adoption. Gillespie, Kim, and Paudel (2007) found no effect, while Prokopy et al. (2008) observed a positive relationship. Lambert et al. (2006) found a positive correlation between farm size and the use of working-land practices supported by voluntary, incentive-based programs such as EQIP. Acres farmed (*ACRES*) is included in the adoption propensity component of the MIMIC model. Presumably, respondents managing more pasture acres relative to the total acres operated (*SHRPAST*) and employing relatively higher stocking rates (*STKRATE*) would be more likely to use PGR or best PM practices.

Dummy variables representing ERS regions are included in the latent variable equations to control for unobserved effects associated with climate, geography, and other region-specific factors. The Southern Seaboard and Fruitful Rim regions are combined into one region (*SOCO*) because of their geographic proximity. Respondents located in the Northern Great Plains and Northern Crescent regions are also combined into a single region (*NORTH*). The Mississippi Portal region is the reference group.

Table 3. MIMIC Estimates for Pasture Management and Prescribed Grazing Adoption by Beef Cattle Farmers

Variables	**Pasture Management (PASTMAN, M)**				**Prescribed Grazing (PGR, P)**		
Indicators	**Est. Coeff.** α_k	λ_k	**Percentage Correct**	**Indicators**	**Est. Coeff.** α_k	λ_k	**Percentage Correct**
WATER	0.838**	0.646***	72.07	*BALANCE*	−0.931	0.985***	72.35
BUFF	−0.685	1.256***	77.93	*ADJUST*	0.156	0.708***	74.72
SHADE	0.757	0.834***	74.33	*LIMIT*	−1.231**	0.757***	67.45
CROSS	−1.594***	0.905***	78.49	*WEED*	0.072	0.320***	63.13
ACCESS	−1.814**	1.546***	83.24	*PADD*	−0.943*	0.891***	71.23
GEOTEX	−3.335***	1.583***	90.22	*GRAZL*	−2.239***	0.867***	76.12
REPLANT	0.000	0.959***	72.49	*BUFFS*	−4.901***	1.894***	87.15
SOILTEST	0.602	1.244***	80.58	*CONSP*	−3.959***	1.614***	83.94
MANURE	−0.319	0.421***	60.48	*GRZHT*	−2.265***	0.992***	75.97
NPK	0.372	0.400***	67.60				

Adoption propensity equation

Indicators	**Est. Coeff.**	**Est. Coeff.**
AGE	0.003	0.008
COLLEGE	0.080	0.187
MEETING	0.094***	0.100***
INTERNET	0.466***	0.302***
PASSON	0.119	0.002
WAIT	−0.159***	−0.134***
GOV	0.035	0.081*
STEWARD	0.103	0.223***
INCLT30	−0.071	−0.020
INC3049	−0.317**	−0.251
INC5099	−0.234**	−0.156
SHRBEEF	0.003**	0.003**
OFF-FARM	−0.258	−0.186
ACRES	−0.002	0.001
SHRPAST	−0.459**	−0.322
STKRATE	0.240***	−0.122
HEART	−0.309	0.002
PRAIR	−0.804***	−0.503**
EAST	−0.175	−0.149
SOCO	−0.011	−0.120
NORTH	−0.682***	0.028
ρ	0.773***	
Log-likelihood	−7,691.79	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Results

The overall model is found to be significant using a log likelihood ratio (LLR) test comparing the estimated model with a model restricting the structural variables to 0. Comparing the ratio of the unrestricted to restricted log-likelihoods, the resulting pseudo-R^2 is 0.39. In addition, a likelihood ratio (LR) test is conducted to test for the bundling of practices into PM and PGR. For this test, a MIMIC model with a single latent variable is estimated. This specification assumes a single

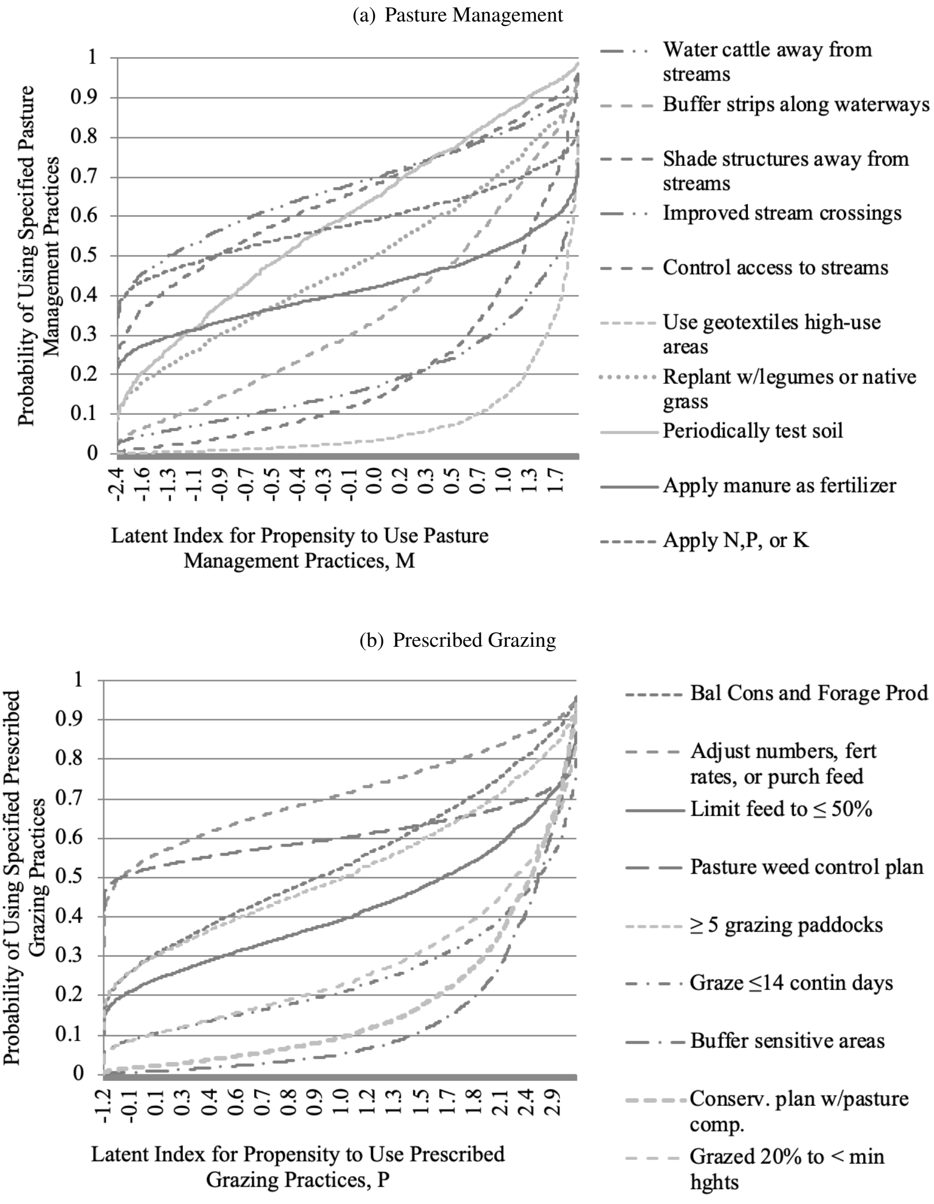

Figure 2. Adoption Curves for Specified Practices and Propensity to Use Management Type by Beef Cattle Farmers

propensity score is sufficient to explain the use of individual technologies in the PM and PGR practice sets. The log-likelihood from this model is compared with that from the model specified in equation (1). The null hypothesis that a single latent variable is sufficient to explain the adoption patterns of both PM and PGR practice sets is rejected. The correlation coefficient associated with the error terms of the latent adoption variables is 0.77 ($p < 0.01$, Table 3). To measure the in-sample predicted accuracy, the percentage of observations correctly classified into their respective categories was calculated for each practice component. For PM practices, the highest percentage the model correctly classified is for *GEOTEX* (90%) and the lowest is for *MANURE* (60%). For the PGR practices, the highest percentage is for *BUFFS* (87%) and the lowest is for *WEED* (61%).

Practice Indicators and Use

The use propensities and corresponding use probabilities are used to generate use curves for each component of the PM and PGR sets of practices (Figure 2). The vertical axes of the figures are the probability of using a specific practice. The horizontal axes are the latent use propensity scores (*M* for *PASTMAN* and *P* for PGR, the η in equation 1). The leading indicators are practices with a high likelihood of use at relatively low levels of use propensity. Examples include watering cattle away from streams, *WATER*, and applying NPK fertilizer). These practices are more likely to be adopted either early in a sequential process of adopting pasture management BMPs or on their own merits and not as part of a broader PM practice bundle. The lagging indicators are those practices for which adoption is indicative of a higher propensity to adopt PM practices. Examples include geotextiles (*GEOTEX*), controlling cattle access to streams (*ACCESS*), improved stream crossings (*CROSS*), and maintaining buffer strips along waterways (*BUFF*). These practices are likely to either appear toward the end of a sequence of PM practice adoption or adopted only by producers who are committed to the adoption of a comprehensive PM program. The leading indicators for PGR are the use of a pasture weed control plan (*WEED*) and adjusting cattle numbers, fertilizer rates, or purchasing feed to offset grazing pressure (*ADJUST*). The lagging indicators for PGR are buffering sensitive areas (*BUFFS*), having a conservation plan with a grazing component (*CONSP*), grazing no more 20% of pasture to less than minimum heights (*GRZHT*), and grazing for no more than 14 continuous days on a single paddock (*GRAZL*).

Operator and Farm Attributes and the Latent Use Variables

While the marginal effects vary from one practice to another, we discuss the average effects across the PM and PGR sets of practices, where significant (Tables 4 and 5). Producers attending an additional Extension meeting per year (*MEETING*) are more likely to use best PM practices, but the marginal effect is relatively small compared to the other significant covariates. For an additional meeting attended by producers, respondents are, on average, 0.1% more likely to use a PM practice. Respondents who used the Internet to make farm management decisions and equipment purchases (*INTERNET*) are, on average, 7.2% more likely to use PM practices. The effect ranges from a 0.042 increase in the likelihood of using commercial NPK products to fertilize pasture (*NPK*) to a 10.3% increase in the probability of using riparian buffers (*BUFF*). Risk-averse producers, as indicated by the variable *WAIT*, are 2.5% less likely to use best PM practices. The marginal effect was largest for the use of riparian buffers (−3.5%) and smallest for the use of NPK fertilizers on pasture (−1.4%). A 1% increase in the share of respondent annual income from beef cattle sales (*SHRBEEF*) translates to a 1.5% increase in the likelihood of using a PM practice.

Respondent participation in extension meetings (*MEETING*) is also positively associated with the propensity to use PGR practices (Table 5). For every additional extension meeting attended by a respondent, the likelihood of using a PGR practice increases by 0.10% on average. Respondents using the Internet to purchase farm equipment or make farm managerial decisions (*INTERNET*) are 4.9% more likely to use a practice associated with PGR. Respondents who tend to wait until other producers adopt technologies (*WAIT*) are 2.2% less likely to use PGR practices. Respondent belief that agencies should encourage the adoption of BMPs through voluntary incentive programs (*GOV*) are 1.3% more likely to use practices associated with PGR. Operators who believe that farmers have a stewardships role in managing farmland (*STEWARD*) are 3.6% more likely to use PGR practices. Producers reporting larger shares of annual income from beef cattle production (*SHRBEEF*) are 1.6% more likely to use PGR practices. Income is not associated with propensity to use PGR practices. Operations located in the Prairie Gateway are 1.8% less likely to use PGR practices than operations located in the Mississippi Portal.

Table 4. Estimated Marginal Effects for Pasture Management Indicator Practices by Beef Cattle Farmers

Variable	*WATER*	*BUFF*	*SHADE*	*CROSS*	*ACCESS*	*GEOTEX*	*REPLANT*	*SOILTEST*	*MANURE*	*NPK*
AGE	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000
COLLEGE	0.010	0.018	0.012	0.011	0.017	0.010	0.015	0.016	0.008	0.007
MEETING	0.000**	0.001**	0.001**	0.000**	0.001**	0.000**	0.001**	0.001**	0.000**	0.000**
INTERNET	0.056***	0.103***	0.070***	0.066***	0.098***	0.058***	0.088***	0.095***	0.046***	0.042***
PASSON	0.014	0.026	0.018	0.017	0.025	0.015	0.023	0.024	0.012	0.011
WAIT	−0.019***	−0.035***	−0.024***	−0.022***	−0.033***	−0.020***	−0.030***	−0.032***	−0.016***	−0.014***
GOV	0.004	0.008	0.005	0.005	0.007	0.004	0.007	0.007	0.003	0.003
STEWARD	0.012	0.023	0.015	0.015	0.022	0.013	0.019	0.021	0.010	0.009
*INCLT*30	−0.009	−0.016	−0.011	−0.010	−0.015	−0.009	−0.014	−0.015	−0.007	−0.006
*INC*3049	−0.038**	−0.070**	−0.048**	−0.045**	−0.067**	−0.040**	−0.060**	−0.065**	−0.031*	−0.029*
*INC*5099	−0.028**	−0.052**	−0.035**	−0.033**	−0.049**	−0.029**	−0.044**	−0.048**	−0.023*	−0.021*
SHRBEEF	0.011***	0.021***	0.014***	0.013***	0.020***	0.012***	0.018***	0.019***	0.009***	0.009***
OFF-FARM	−0.031	−0.057	−0.039	−0.037	−0.054	−0.032	−0.049	−0.053	−0.026	−0.023
ACRES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SHRPAST	−0.055**	−0.102**	−0.069**	−0.065**	−0.096**	−0.058**	−0.087**	−0.093**	−0.045**	−0.042**
STKRATE	0.029***	0.053***	0.036***	0.034***	0.050***	0.030***	0.046***	0.049***	0.024***	0.022***
HEART	−0.037	−0.068	−0.046	−0.044	−0.065	−0.039	−0.059	−0.063	−0.030	−0.028
PRAIR	−0.096***	−0.178***	−0.121***	−0.114***	−0.169***	−0.101***	−0.152***	−0.164***	−0.079***	−0.073***
EAST	−0.021	−0.039	−0.026	−0.025	−0.037	−0.022	−0.033	−0.036	−0.017	−0.016
SOCO	−0.001	−0.003	−0.002	−0.002	−0.002	−0.001	−0.002	−0.002	−0.001	−0.001
NORTH	−0.082***	−0.151***	−0.103***	−0.097***	−0.143***	−0.086***	−0.129***	−0.139***	−0.067**	-0.062**

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 5. Estimated Marginal Effects for Prescribed Grazing Indicator Practices

Variable	*BALANCE*	*ADJUST*	*LIMIT*	*WEED*	*PADD*	*GRAZL*	*BUFFS*	*CONSP*	*GRZHT*
AGE	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.001
COLLEGE	0.036	0.023	0.031	0.014	0.034	0.029	0.038	0.039	0.034
MEETING	0.001**	0.000**	0.001**	0.000*	0.001**	0.000**	0.001**	0.001**	0.001**
INTERNET	0.058***	0.037***	0.049***	0.022***	0.055***	0.047***	0.061***	0.063***	0.055***
PASSON	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WAIT	−0.026***	−0.016***	−0.022***	−0.010**	−0.024***	−0.021***	−0.027***	−0.028***	−0.024***
GOV	0.015*	0.01*	0.013*	0.006*	0.015*	0.013*	0.016*	0.017*	0.015*
STEWARD	0.042***	0.027**	0.036***	0.016**	0.04***	0.035***	0.045***	0.046***	0.040***
INCLT30	−0.004	−0.002	−0.003	−0.001	−0.004	−0.003	−0.004	−0.004	−0.004
INC3049	−0.048	−0.031	−0.041	−0.018	−0.046	−0.039	−0.050	−0.052	−0.045
INC5099	−0.030	−0.019	−0.026	−0.011	−0.028	−0.024	−0.031	−0.032	−0.028
SHRBEEF	0.019***	0.012***	0.016***	0.007***	0.018***	0.016***	0.020***	0.021***	0.018***
OFF-FARM	−0.035	−0.023	−0.030	−0.013	−0.034	−0.029	−0.037	−0.039	−0.034***
ACRES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SHRPAST	−0.061	−0.039	−0.053	−0.023	−0.058	−0.05	−0.065	−0.067	−0.058
STKRATE	−0.023	−0.015	−0.020	−0.009	−0.022	−0.019	−0.025	−0.025	−0.022
HEART	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PRAIR	−0.096**	−0.061**	−82.000**	−0.037**	−0.091**	−0.079**	−0.101**	−0.104**	−0.091**
EAST	−0.028	−0.018	−0.024	−0.011	−0.027	−0.023	−0.030	−0.031	−0.027
SOCO	−0.023	−0.015	−0.020	−0.009	−0.022	−0.019	−0.024	−0.025	−0.022
NORTH	0.005	0.003	0.005	0.002	0.005	0.004	0.006	0.006	0.005

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

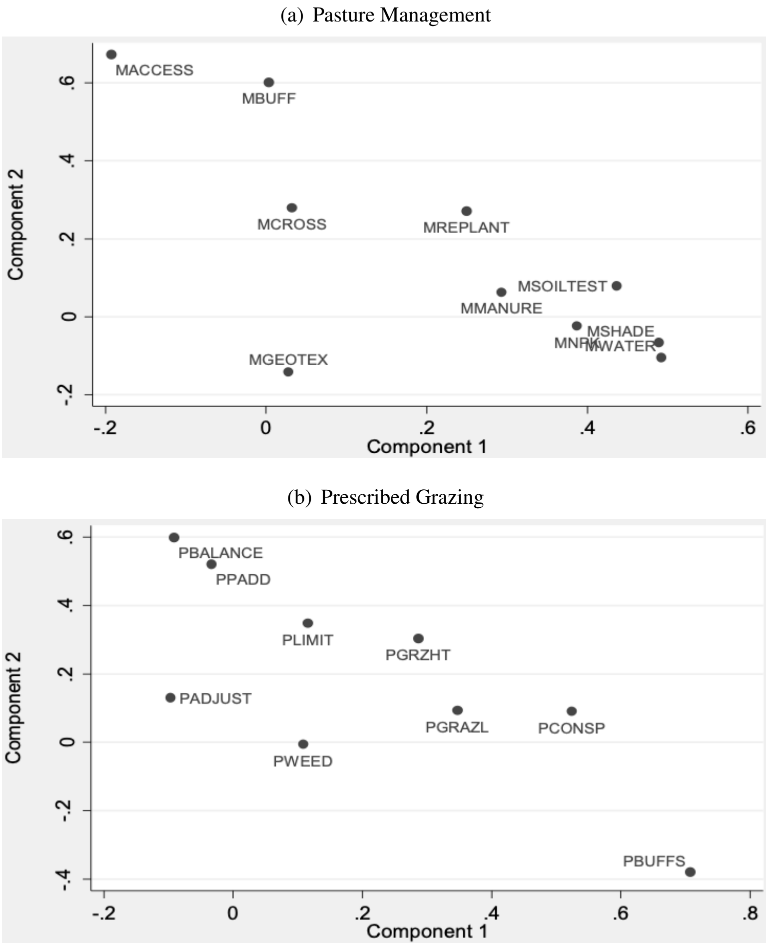

Figure 3. Loadings from the PCA of Predicted Probabilities of Adopting Pasture Management and Prescribed Grazing Practices by Beef Cattle

Notes: Rotation: oblique quartimin

Producers reporting incomes in the highest income category are more likely to use a PM practice. Respondents managing relatively more of their farmland as pasture (*SHRPAST*) are 7.1% less likely to use PM practices, but operators utilizing higher stocking densities (*STKRATE*) are 0.04 more likely to use one or more of the PM technologies. Compared to producers in the Mississippi Portal region, cattle operations in the Prairie Gateway and Northern Great Plains regions are 12.5% and 10.6% less likely, respectively, to use PM practices.

Bundle Clustering

The *ex post* analysis of practice bundles suggests there is a significant decline in eigenvalues after three principal components. Based on the first two principal components, the use probabilities cluster around a bundle of best PM practices and a bundle of PGR practices. To evaluate further the clusters in each practice set, a PCA was conducted for each bundle of practices separately (Figure 3). The loadings for pasture management suggest that most PM practices group together, with the use of geotextiles, stream crossings, limiting cattle access to streams, and establishing buffer strips along waterways being exceptions to this grouping. These practices orient toward water quality and soil erosion. For the PGR practices, all appear to bundle except for buffering-sensitive areas. Programmatically, these findings could raise questions about the effects of including practices that focus on protection of waterways and reducing erosion on producer willingness to adopt a predetermined package of practices, such as PGR. These findings are similar to those by Gillespie, Kim, and Paudel (2007) and Kim, Gillespie, and Paudel (2005) that farmers were more likely to adopt practices with more immediate pecuniary benefits than those with less evident pecuniary benefit but longer term environmental benefits.

Conclusions

This research used a bivariate MIMIC model to examine the use patterns of best PM and PGR practices among beef cattle producers east of the 100th meridian. The most commonly used PM practices were off-stream cattle watering, installing shade structures away from streams, periodic soil testing, and applying NPK fertilizer to pastures. The most commonly used PGR practices were adjusting livestock numbers, fertilizer rates or purchased feed to meet livestock needs and using a weed control plan. The least popular PM practices were protecting heavy use areas with geotextile, installing stream crossings, and controlling access to streams. The least popular PGR practices were buffering sensitive areas in paddocks, following a conservation plan that includes a grazing component, grazing livestock for no more than 14 continuous days on a paddock, and grazing no more than 20% of pasture to less than minimum grazing heights. While more PM practices fell into the highly used category, the overall average use rates were 53% for the PM practices and 52% for the PGR components. A pattern or sequence of practice use is apparent, as evidenced by graphical analysis. Further research could include survey questions that ask producers when they adopted each practice or component, which could more clearly explain the cumulative adoption curves and the clear positive correlation between the components of both practice sets. Similarly, respondents could be asked whether they previously adopted and abandoned any of the practices, which would allow for examination of the effects of practice abandonment on current use patterns. A limitation of the bivariate MIMIC model applied here is that it models these relationships as discrete correlated events and cannot account for the sequence in which a producer adopts these practices.

Taken together, these results suggest that PGR and PM practices are complementary, with each set appealing to an identifiable group of producers even after controlling for producer and farm business explanatory variables. While the complementarity among the groups is perhaps unsurprising—as these practices could be expected to be parts of an overall PM program—further research could expound on the reasons and implications of the distinct bundling of PM and PGR practices.

An *ex post* PCA analysis of the use probabilities revealed that some practices are less compatible than others with current PM practices. Across both PM and PGR, these practices focused on stream crossing structures and creating riparian buffers. These "outlier practices" are among those that tended to be used less (or not at all) rather than more broadly among the practices. Given that these practices have substantial off-farm benefits, it may be that producers will require higher incentive levels to adopt them. Prior research (Gillespie, Kim, and Paudel, 2007; Kim, Gillespie, and Paudel, 2005) suggests farmers are less likely to adopt these types of practices. Thus, agencies looking to bundle practices into a system might choose to exclude them to boost producer participation rates. An agency could then offer a higher incentive for these practices, either individually or as a bundle. Alternatively, an agency might attempt to segment the market by creating PGR packages with and without the buffering sensitive areas practice and providing different incentive levels for the two packages. Future research could address these questions.

In examining the effects of the structural variables on propensity to adopt, the associations with most of the covariates are as expected. However, some interesting patterns emerged. Four covariates had a significant influence on propensity to adopt PM but not PGR. These covariates relate to the farm business or its structure (e.g., farm income, income from beef, share of land in pasture, and stocking rates). However, the two variables that are correlated with the propensity to adopt PGR are attitudinal and related to the environment, perhaps more illustrative of an ideological motivation for PGR adoption (e.g., belief that the government should provide incentives for farmer adoption of conservation practices and belief that farmers are stewards of the land). These results may suggest that a comprehensive PM program is more likely to appeal to producers with the resources to expend on adopting BMPs, while the PGR program is more likely to appeal to those preferring low-environmental-impact grazing systems.

Finally, the MIMIC model is a potential alternative to modeling producer survey responses concerning BMP use when respondents are presented a suite of practices that could be interrelated or simultaneously adopted. The bundles identified with PCA based on the use propensities could differ from those identified with another estimation method. A more rigorous comparison between MIMIC models or, for example, a multivariate probit regression relating technology use and farmer characteristics, would entail a comparison of the small sample properties of both estimation methods in a Monte Carlo experiment. The experiment would entail defining preidentified clusters and proceed by comparing how well the MIMIC model performs with a challenger.

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