Use of Weather Information for Agricultural Decision Making

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ABSTRACT

This study uses data from a special subsample of the National Agricultural, Food, and Public Policy Preference Survey to assess use of weather data for agricultural decision making. Responses from 284 Arizona farmers and ranchers were used to examine (i) the importance producers placed on different types of weather data for production and marketing decisions; (ii) which producer characteristics accounted for differences in the importance they placed on weather data; (iii) producer use of weather data for specific production and marketing decisions; and (iv) which factors distinguish weather data users from nonusers. A model of demand for weather information was developed and used to specify count data and discrete choice multivariate regression models. The intensity of weather data use was greater among producers with diversified agricultural production. Diversified producers were more likely to use data for timing of planting, cultivation, and harvest. Weather data use was lower among producers with greater reliance on off-farm income. Producers who rated government risk-management programs as important also found more weather data types important and used weather data for more decisions. Access to satellite TV increased data use but access to the Internet did not.

1. Introduction

Assessing the value of weather information is a discrete-continuous choice problem. First, there is the discrete choice of whether to use any weather information. If so, continuous problems include the intensity and returns to information use. Much of the literature on the value of weather information focuses on estimating the benefits of information use, given that the choice of use is already made (Stewart 1997; Wilks 1997). However, as Freebairn and Zillman (2002) note, ''studies find that a significant proportion of potential users do not use meteorological services in decision-making (p. 40).''

This article uses data from a survey of Arizona farmers and ranchers to examine the initial discrete choice of weather data use. In it, we (i) introduce a discrete choice framework, illustrating the relationship between information valuation and use; (ii) discuss the survey instrument and weather use data; (iii) present the econometric specifications and explanatory variables used in regression analyses (regressions are used to test hypotheses concerning determinants of weather data use); (iv) discuss results; and (v) summarize main findings and suggests areas of future research.

2. Empirical specification

Here, we introduce a discrete choice framework that treats acquisition and use of weather data as part of an agricultural decision-maker's utility function. Utility is a measure of benefit or satisfaction the producer derives. Information use is a choice variable (Stigler 1961) and its acquisition involves cost (Feder and Slade 1984). Using weather data can be costly monetarily (e.g., expenses for subscriptions to information services) or in terms of household time (to acquire and process information).

Consider an agricultural producer who must make multiple production and marketing decisions throughout the year whose outcomes depend on weather conditions. The producer may be able to use weather data to make better decisions (i.e., decisions with outcomes the producer prefers). Let $\boldsymbol{\delta}$ represent a vector of n decisions, and $\mathbf{w}$ represent a vector of m types of weather data. For

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each decision δ_i a producer may use a type of weather data w_j such that $\delta_i = \delta_i(w_1, w_2, \ldots w_m)$. This can be treated as an integer programming problem so that $w_i = 1$ if the data is used and $w_i = 0$ if not. One can express the producer's utility as

$$U = U(u_1\{\mathbf{y}[\boldsymbol{\delta}(\mathbf{w}), \mathbf{x}, \mathbf{z}(\mathbf{w})], \sigma_y[\boldsymbol{\delta}(\mathbf{w}), \mathbf{x}, \mathbf{z}(\mathbf{w}), r], c[\boldsymbol{\delta}^w, \mathbf{x}, \mathbf{z}(\mathbf{w})], n\}, u_2[\boldsymbol{\delta}(\mathbf{w}), \mathbf{x}, \mathbf{z}(\mathbf{w}), \boldsymbol{\omega}]), \quad (1)$$

where

- $\mathbf{y}$ = a vector of incomes from sales of different agricultural commodities;
- $\mathbf{x}$ = a vector of operator or operation characteristics that are invariant to weather data use;
- $\mathbf{z}(\mathbf{w})$ = a vector attributes associated with the extent of weather data use;
- σ_y () = a function capturing effects of household income variability;
- r = an indicator of attitudes toward income risk;
- $c()$ = a cost function measuring monetary and nonmonetary costs of using weather data;
- n = nonfarm income;
- u_1 = a utility subfunction that depends on income, income variability, and costs of weather data use;
- u_2 = another utility subfunction where weather data is evaluated in terms of external and/or nonmonetary considerations; and
- ω = vector of external or nonmonetary considerations such as environmental stewardship or conforming to social norms, preferences of other household members, or expert recommendations.

The subfunction u_1, in the overall utility function, has the elements of a standard (expected) utility function of neoclassical economics, where utility depends on household income and income variability. Different approaches may used to examine household preferences in response to uncertain and variable outcomes. While expected utility models assume cases where probabilities are known, subjective expected utility models address the more realistic case where the decision maker does not know what underlying probabilities are. Other approaches include prospect theory and regret theory [Shaw and Woodward (2008) provide further discussion]. We do not impose a specific functional form on u_1 implied by competing theories. At this stage, we simply acknowledge that variability and uncertainty matter to the decision maker.

The subfunction u_2 acknowledges that, while household income and income variability are important considerations, they are not the sole factors influencing producer use of weather data. A few studies have combined a simplified version of u_1 (where farm income is the only argument) with a "behavioral" function, such as u_2, to test hypotheses about adoption of conservation measures (Bishop et al. 2010; Chouinard et al. 2008; Sheeder and Lynne 2011). They test this theory through discrete choice regression analysis, where the adoption regression depends on a reduced form specification of utility $V = V(\mathbf{x}, \boldsymbol{\omega})$. The papers find that many variables equivalent to $\boldsymbol{\omega}$ above are individually, statistically significant and that the predictive power of the models improve when these behavioral variables are included. Equation (1) further acknowledges that farm-level decisions about weather data use are not necessarily made by a single individual in isolation of considerations of—and input from—household members, business partners, fellow producers, neighbors, media sources, or farm consultants (Hu et al. 2006).

To test hypotheses about weather data use, we rewrite (1) as a reduced-form random utility model. Utility when a producer does not use weather data type w_i is

$$U_0 = u[w_{i0}, \mathbf{x}, \mathbf{z}(w_{i0}), r, n, \boldsymbol{\omega}] + \varepsilon[\mathbf{x}, \mathbf{z}(w_{i0}), r, n, \boldsymbol{\omega}.\mathbf{e}_{i0}], \quad (2)$$

where u and ε are real valued functions. The vector $\mathbf{e}_{i0}$ represents unmeasured attributes of the producer or the producer's operation. Utility when a producer uses weather information is

$$U_1 = u[w_{i1}, \mathbf{x}, \mathbf{z}(w_{i1}), r, n, \boldsymbol{\omega}] + \varepsilon[\mathbf{x}, \mathbf{z}(w_{i1}), r, n, \boldsymbol{\omega}, \mathbf{e}_{i1}], \quad (3)$$

where $\mathbf{e}_{i1}$ is a vector of unmeasured attributes of the producer, the operation, and the weather data used. If the population is drawn from a random sample with common socioeconomic characteristics, the vectors $\mathbf{e}_{i0}$ and $\mathbf{e}_{i1}$ will be random, and the utility function value will be stochastic (Domencich and McFadden 1975). We therefore assume that the random components can be expressed as $\boldsymbol{\varepsilon}(\mathbf{e}_{i0})$ and $\boldsymbol{\varepsilon}(\mathbf{e}_{i1})$.

The value of weather information V^* can be expressed as

$$V^* = u[w_{i1}, \mathbf{x}, \mathbf{z}(w_{i1}), r, n, \boldsymbol{\omega}] + \varepsilon(\mathbf{e}_{i1}) - u[w_{i0}, \mathbf{x}, \mathbf{z}(w_{i0}), r, n, \boldsymbol{\omega}] + \varepsilon(\mathbf{e}_{i0}). \quad (4)$$

A utility-maximizing producer will use weather information if there is a net gain in utility of doing so. In other words, the producer will use information if the value of doing so is positive:

$$V^* = \{u[w_{i1}, \mathbf{x}, \mathbf{z}(w_{i1}), r, n, \boldsymbol{\omega}] - u[w_{i0}, \mathbf{x}, \mathbf{z}(w_{i0}), r, n, \boldsymbol{\omega}]\} - [\varepsilon(\mathbf{e}_{i1}) - \varepsilon(\mathbf{e}_{i0})] > 0. \quad (5)$$

If farm income were a small share of farm household income, then weather-related farm risk would be less important to the household. In contrast, as farm income makes up a greater share of total household income, weather-related agricultural risk grows in importance.

The value of information V^* is not observed. However, we observe the discrete choice V (weather information used or not used). If $\varepsilon(\mathbf{e}_{i1})$ and $\varepsilon(\mathbf{e}_{i1})$ are each normally distributed then their difference $u = \varepsilon(\mathbf{e}_{i1}) - \varepsilon(\mathbf{e}_{i0})$ is also normally distributed. If we assume that $\{u[w_{i1}, \mathbf{x}, \mathbf{z}(w_{i1}), r, n, \boldsymbol{\omega}] - u[w_{i0}, \mathbf{x}, \mathbf{z}(w_{i0}), r, n, \boldsymbol{\omega}]\}$ can be written as a linear function of variables, then

$$V^* = \boldsymbol{\alpha}'\mathbf{x}_i + \boldsymbol{\beta}'\mathbf{z}(w_{i1}) + \boldsymbol{\gamma}'\mathbf{z}(w_{i0}) + \rho r + \eta n + \nu, \quad (6)$$

where $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, ρ, and η are regression coefficients and

$$V = 1 \quad \text{if} \quad V^* > 0 \quad \text{and} \quad V = 0 \quad \text{otherwise}. \quad (7)$$

If ν is normally distributed, this is the standard form of a probit regression (Maddala 1983).

Much of the literature on the value of weather information focuses on estimating value of information to users. Our binary choice model produces negative economic information of sorts. By distinguishing between users and nonusers of data, it distinguishes between agricultural producers that expect a net benefit from using weather information from those that do not. While we cannot obtain estimates of the value of V^* for producers where $V = 1$, we can infer that $V^* \leq 0$ for nonusers. In other words, we can identify characteristics of producers who do not derive expected benefits from weather data.

The reduced form regression Eq. (5) captures the discrete choice of using a particular type of weather data but does not necessarily link use to a specific decision (i.e., a single type of data could inform multiple decisions). The econometric specification could also be framed in terms of decisions $\boldsymbol{\delta}$. In this case, the observed discrete choice is the use of some kind of weather data for the particular discrete decision δ_i. Our survey contains questions about producers' assessment of the importance of types of data w_j and the use of some kind of weather data for specific decisions δ_i.

A growing number of practitioners are using contingent valuation (CV) surveys to directly elicit user willingness to pay (WTP) for meteorological information and services (Anaman and Lellyett 1996; Anaman and Lellyett 2007; Chapman 1992; Rollins and Shaykewich 2003; Stratus Consulting Inc. 2002). Freebairn and Zillman (2002) note that many respondents in CV studies report a zero WTP. They note that this finding is consistent with separate empirical studies of weather data use, which often find that many respondents do not use the weather data in question. This makes sense—people do not use services they do not value. With many zero-value responses, WTP data will be "right censored" with a probability spike at zero. Probit analysis, therefore, can identify some of the factors that account for zero-value responses.

Just et al. (2002) focus on the importance of three types of heterogeneity in considering demand for economic information in agriculture—heterogeneity with respect to (i) decision-maker attributes, (ii) information sources (providers), and (iii) the nature of the information itself. Just et al. (2002) stress the difference between raw, unprocessed data, and information that intermediaries translate for end users. Jones et al. (1989) stress the difference between general and specific information as well as differences between public and private sources. These forms of heterogeneity may be important for agricultural demand for weather information as well. In principle, the econometric specification can deal with all these types of heterogeneity.

The cost of acquiring and processing information depends on technology. Many providers of climate services have stepped up development of web-based information and decision-tools (Pasteris et al. 2004; Jensen et al. 2000; Breuer et al. 2008). This begs the question, "what about farmers and ranchers who do not use computers or have Internet access?" According to the most recent U.S. Department of Agriculture (USDA) Farm Computer Usage and Ownership survey (U.S. Department of Agriculture National Agricultural Statistics Service 2009), 41% of farms did *not* have Internet access, while 64% of farms did *not* use computers for business. Among farms with \$100 000 (monetary values in U.S. dollars throughout) or more in annual sales, 70% have Internet access, while 61% use computers for business. These figures suggest two things. First, a digital divide may be opening between large and small farms. Second, even among larger-scale producers, a significant share is not yet in a position to use web-based meteorological services directly. One question explored in this study is whether Internet access has had important effects on farmer and rancher use of weather data.

3. The survey and weather data

Data come from Arizona responses to the National Agricultural, Food, and Public Policy Preference Survey (Lubben et al. 2006). USDA's National Agricultural Statistics Service (NASS) administered the survey from late 2005 to early 2006 in 27 states, with support from the Farm Foundation. The survey was a random sample, stratified by farm income. It included questions common to each participating state, optional questions asked in a subset of states, and a set of state-specific questions. Cooperative Extension Specialists in each state, in conjunction

TABLE 1. Applications of weather data to agricultural decisions. Adapted from Pasteris et al. (2004).

Type of weather data	Agricultural decisions
Temperature	Planting, harvesting, defoliation, crop modeling, disease risk, shelter animals, pest control, sheep shearing
Precipitation	Planting, harvesting, fertilizer applications, cultivation, spraying, irrigation, disease risk, livestock and poultry protection
Soil moisture	Planting, harvesting, fertilizing, transplants, spraying, irrigation, monitoring of growing conditions, measuring plant stress
Soil temperature	Planting, pest overwintering conditions, transplanting, fertilizing
Frost	Pest overwintering conditions, Protect crops from damage, animal sheltering, irrigation (to avert crop damage)
Degree days	Planting, irrigation, pest control
Relative humidity	Harvesting, pollination, spraying, drying conditions, crop stress potential
Wind speed	Defoliation, harvesting, freeze potential/ protection, animal sheltering, shelter, pest control, pruning, spraying or dusting, pollination, dust drift, pesticide drift
Wind direction	Freeze potential/protection, cold or warm air advection over crop areas, pesticide drift, dust drift

with NASS, developed state-specific questions. Most questions concerned agricultural producer attitudes about current or potential farm legislation. Other questions concerned farm program participation, personal characteristics (e.g., age, education), and operation characteristics (e.g., total sales, commodity specialization).

The Arizona survey included two questions related to weather data (Table 1). The first asked producers to indicate the importance of different weather data for their production or marketing decisions. Producers could respond on a 5-point Likert scale (least important, less important, neutral, important, and most important). Producers could also choose ''don't know/no opinion'' although this choice was exceedingly rare. The second question asked producers whether they used weather information to make different production or marketing decisions (such as timing irrigation, moving livestock, or timing harvest). Table 1 lists management decisions that may make use of weather types from the survey.

While the Arizona sample of the survey had more than 300 valid responses, we present results of a subsample of 284 producers with complete responses for weather variables and variables subsequently used in multivariate regressions. Reported producer attributes and responses to weather data questions did not differ significantly between the full sample and this subsample. Comparing both full and subsample responses with Arizona data from the 2002 Census of Agriculture, the policy preference survey modestly oversamples producers with greater agricultural sales.

Figure 1 shows the percentage of respondents that indicated a particular type of weather data was either ''important'' or ''most important.'' For the rest of the article, we will use the word ''important'' to include both categories. Most producers found data on soil temperature (67%) temperature (64%), and frost (56%) important, while relatively few found wind speed (30%) or wind direction (12%) important (Fig. 1).

Figure 2 compares assessments of weather data importance for three producer groups:

- 105 Crop Producers, who have crop sales, but no reported livestock sales (37% of sample);
- 141 Livestock Producers, with livestock sales, but no reported crop sales (50% of sample); and
- 38 Diversified Producers, who have both crop and livestock sales (13% of sample).

Diversified producers were more likely to report a given type of data important than crop or livestock producers. Except for soil moisture, livestock producers were least likely to report a type of weather data important. Here still, diversified producers were most likely to report soil moisture as important. Fewer than half of producers (45%) found precipitation data important (Fig. 1). However, this figure was higher for crop (60%) and diversified producers (55%) than for livestock producers (32%).

Use of weather data for management decision varied significantly by producer group (Fig. 3). Largely, this is because of the nature of the data-use questions. Nine of the decisions (crop choice, crop variety choice, timing planting(s), timing cultivation, timing pesticides, timing irrigation, timing harvest, and crop storage, and crop insurance) relate almost exclusively to crop production, while three (livestock grazing, moving livestock, and livestock pest control) are exclusive to livestock production. Crop/livestock sales, in principle, could apply to any of the three groups, although few crop producers reported using weather data for this decision. Hedging could also apply to either crop or livestock sales, but few producers of any type used weather data to inform this decision.

Thus, one might expect that diversified producers use weather data for crop-specific decisions in much the same way as crop producers and data for livestock-specific decisions in much the same way as livestock producers. For the most part, Fig. 3 bears this out. Notably, however, diversified producers have slightly higher rates of using

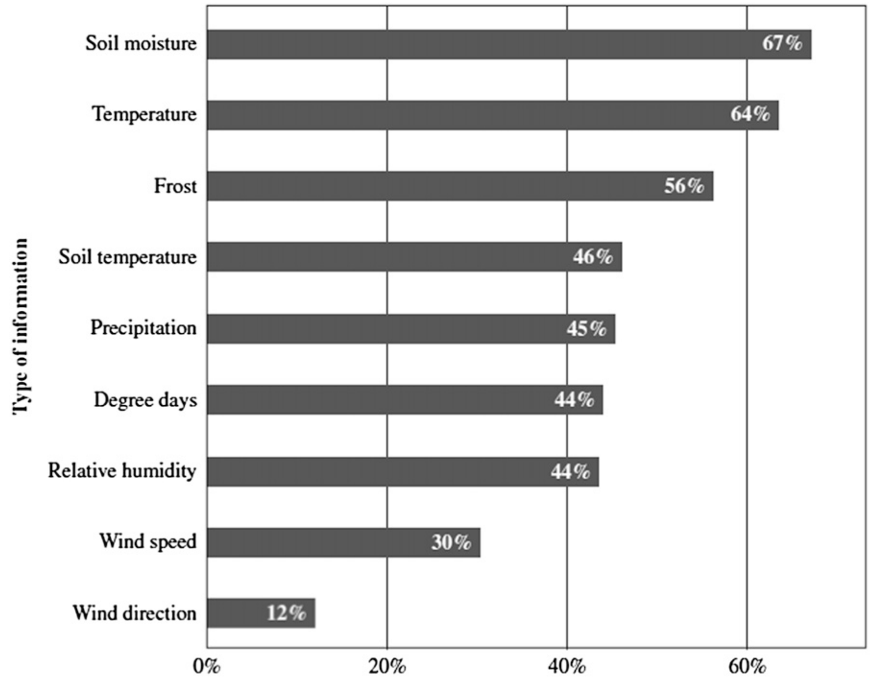

FIG. 1. Agricultural producer importance ratings of weather data for production and marketing decisions.

weather data for timing of harvest, timing of cultivation, crop variety choice (which also may have a timing element in terms of length of season or planting date), and for crop storage.

Some crop producers report weather data for some livestock-specific decisions, while some livestock producers use weather data for crop-specific decisions (Fig. 3). Three factors might account for this. First, livestock

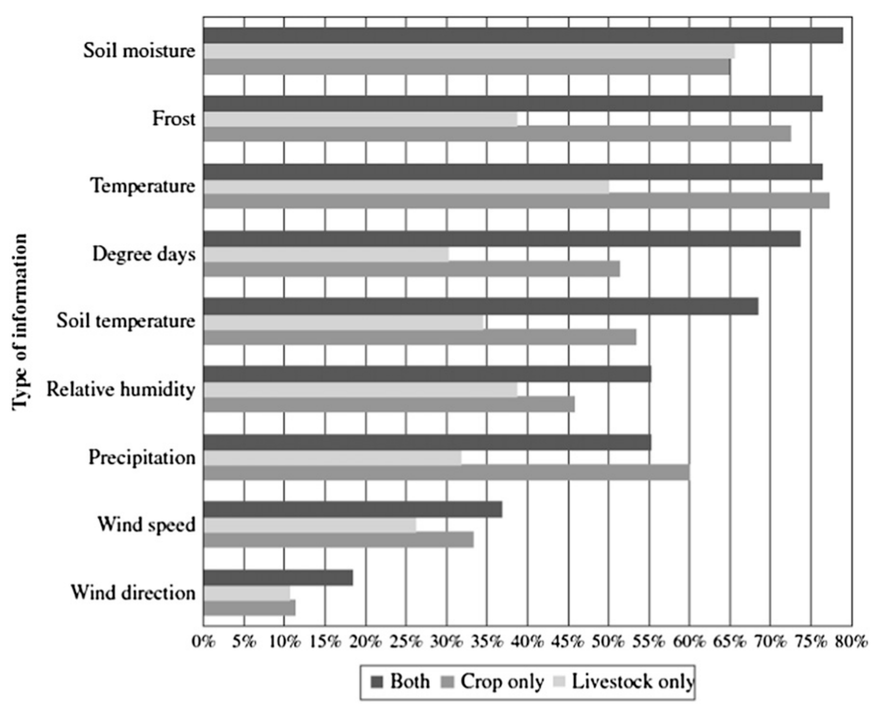

FIG. 2. Importance rating of weather data by producer type.

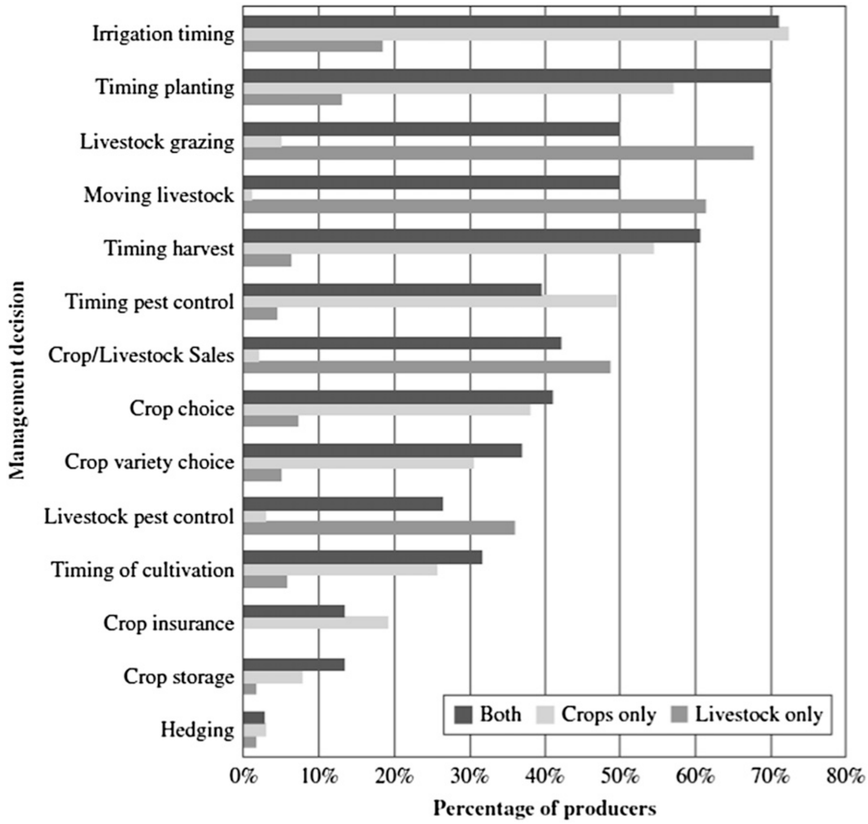

FIG. 3. Use of weather and climate data by producer type.

producers could have irrigated pasture (and hence use weather data to time irrigation applications). Second, livestock producers may grow forage crops, not for sale, but for use by their animals. Third, some crop producers may have livestock, but no livestock sales in the survey year. According to the *2007 Census of Agriculture*, Arizona had 7716 operations with cattle and calf inventories but only 4078 with cattle and calf sales.

Two summary indices were created for the weather data. The first is a weather data use index. This is the total number of agricultural decisions (from Table 2) for which a producer used weather data. The index could take on an integer value from 0, 1, 2, . . . , 14. Similarly, a weather data importance index is the total number of weather data types a producer found important or most important (also from Table 2). This could take on integer values 0, 1, 2, . . . , 9. The average value of the data use index was 3.5, while the average value for data importance was 4.1 (Fig. 4). As in Figs. 2 and 3, these indices vary by producer group. Diversified producers use data for more decisions. This is not surprising because, by definition, they have more decisions to make. Diversified producers, however, also use more total types of weather data. In addition, diversified producers tended to use weather data for crop-specific decisions more than crop producers did (Fig. 3).

4. Econometric models

We conducted multivariate regression analysis on the indices for weather data use and weather data importance. Our interest was to see what factors explain differences in the total number of data types found important and the total number of agricultural decisions for which producers used weather data. We also estimated nine separate probit multivariate regressions for each individual data type. Here, the dependent variables equaled one if a producer rated a data type "important" or "most important" and equaled zero otherwise. In the context of the regression model Eqs. (5) and (6) above, we do not observe that value respondents place on a type of weather data. We do, however, observe whether they rate that data as important for making decisions. We thus assume that respondents place a higher value on a data type that they rate as important (as opposed to unimportant). Separate probit regressions were also run for data use variables. Here, the dependent variables equaled one if a producer used weather data for a particular agricultural management decision and zero otherwise.

TABLE 2. Weather survey questions from the Arizona sample of the 2005/06 National Agricultural, Food, and Public Policy Preference Survey.

Please indicate how important the following weather data are for your production and marketing decisions [(1 = least important (LI), 2 = less important, 3 = neutral, 4 = important, 5 = most important (MI), X = don't know/no opinion (DK)]

	LI				MI	DK
	1	2	3	4	5	X
a. Temperature	1	2	3	4	5	X
b. Precipitation	1	2	3	4	5	X
c. Wind speed	1	2	3	4	5	X
d. Wind direction	1	2	3	4	5	X
e. Soil moisture	1	2	3	4	5	X
f. Soil temperature	1	2	3	4	5	X
g. Frost/freeze conditions	1	2	3	4	5	X
h. Degree days	1	2	3	4	5	X
i. Relative humidity	1	2	3	4	5	X

Do you use weather information (such as temperature, precipitation, humidity, degree days, wind speed, frost/freeze conditions) for any of the following production or marketing decisions? (Check all that apply)

Crop choice	☐	Crop variety choice	☐
Timing planting(s)	☐	Timing cultivation	☐
Timing pesticides	☐	Timing irrigation	☐
Timing harvest	☐	Crop insurance	☐
Crop/livestock sales	☐	Crop storage	☐
Hedging	☐	Livestock grazing	☐
Moving livestock	☐	Livestock pest control	☐

The indices for weather data use and importance are count data. The data use index is a count of the total number of data types a producer deems important or most important. The importance index is the total number of decisions for which producers used weather data. In both cases, the dependent variables (the counts) are integers. Because these variables are discrete integers rather than continuous variables, standard least squares regression is not appropriate (Cameron and Trivedi 1998; Gardner et al. 1995). We instead fit negative binomial regressions to the data.

Regression explanatory variables

The following explanatory variables were included in the regression. First, there were six (0/1) farm sales-class variables. The default (omitted) category was operations below $10 000. The highest sales class included operations with sales of $1 million or more. Next, three dummy variables indicated producer age (45–54, 55–64, and 65 and older), while two accounted for education (college degree, advanced degree). Dummy variables also indicated if a producer was male, Hispanic, had e-mail access, had a satellite television, or owned 50% or more of operated farmland. Three variables also distinguished producers by farm income as a share of household income (26%–50%, 51%–75%, and 76%–100%).

As part of the policy preference portion of the survey, producers were asked to rate the importance of maintaining funding for various USDA programs. Another dummy variable equaled one if producers rated maintenance of government risk-management programs (crop and livestock insurance programs) as important or most important.

To measure farm diversification, dummy variables were included distinguishing crop producers (crop sales only) and diversified producers (crop and livestock sales) from the default, livestock producers (livestock sales only). We also experimented with measures of farm diversification

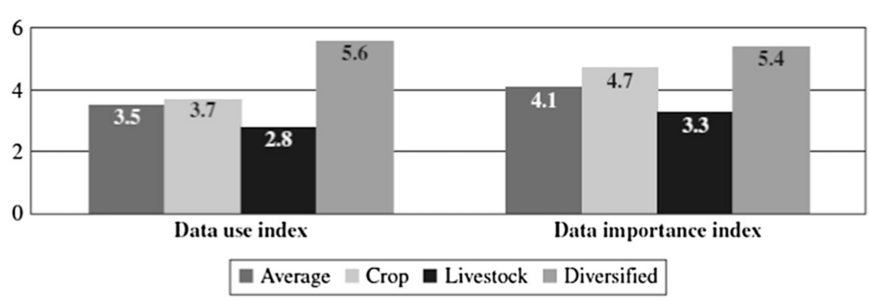

FIG. 4. Indices of weather data use and importance by producer type.

TABLE 3. Negative binomial regressions for weather data importance and weather data use indices.

	Weather Data Importance Index[a]		Weather Data Use Index[b]	
	Coefficient	$\lvert t \text{ ratio}\rvert$	Coefficient	$\lvert t \text{ ratio}\rvert$
Diversified producer (0/1)	0.298[c]	2.04	0.560[d]	4.52
Crop producer (0/1)	0.339[d]	3.40	0.305[d]	3.15
Number of commodities sold	0.0856	1.53	0.137[d]	2.61
Avg sales ($10 000–$49 999)	0.0789	0.63	−0.119	0.98
Avg sales ($50 000–$99 999)	−0.0354	0.22	−0.118	0.75
Avg sales ($100 000–$249 999)	0.0911	0.59	−0.0837	0.58
Avg sales ($250 000–$499 999)	−0.0151	0.08	−0.462[c]	2.29
Avg sales ($500 000–$999 999)	0.123	0.57	−0.313	1.56
Avg sales ($1 000 000 and over)	0.151	0.80	−0.399[c]	2.20
Age (45–54)	0.336[c]	2.20	0.281[c]	2.01
Age (55–64)	0.279[e]	1.79	0.0738	0.51
Age (65 and over)	0.432[d]	2.84	0.0873	0.61
Male (0/1)	−0.006 79	0.05	−0.037	0.29
Bachelor's degree (0/1)	0.001 23	0.01	−0.008 47	0.08
Advanced degree (0/1)	0.0225	0.17	0.175	1.37
Farm income/total income (26%–50%)	0.146	1.13	0.357[d]	2.86
Farm income/total income (26%–50%)	−0.000 88	0.01	0.351[c]	2.46
Farm income/total income (76%–100%)	0.149	1.06	0.471[d]	3.48
Hispanic (0/1)	0.133	0.89	0.245[e]	1.72
Avg land owned >50% (0/1)	−0.279[d]	2.66	−0.239[c]	2.39
E-mail access (0/1)	−0.0509	0.57	0.0942	1.07
Satellite TV (0/1)	0.173[c]	2.10	0.181[c]	2.27
Risk management important (0/1)	0.145[e]	1.76	0.135[e]	1.71
Constant	0.705[d]	3.11	1.044[d]	3.36
Ln (α)	−1.853[d]	6.80	−2.455[d]	6.25
Observations	284		284	

[a] The dependent variable is an integer count from 0 to 9 of the total number of weather data types a producer rated ''important'' or ''most important'' for production and marketing decisions.

[b] The dependent variable is an integer count from 0 to 14 of the total number production and marketing decisions for which a producer used weather data.

[c] Significant at 5% level.

[d] Significant at 1% level.

[e] Significant at 10% level.

discussed by Pope and Prescott (1980). The one that proved significant in regressions was the total number crop and livestock categories for which the producer reported sales. The survey asked producers to allocate sales shares between 12 crop and 7 livestock categories. This diversification variable, thus, accounts for diversification within crop and livestock production categories.

With a relatively large number of explanatory variables (>20) in the regressions, there is the possibility that collinearity between those variables will inflate estimated standard errors and compromise the overall reliability of results (Belsley et al. 1980). Based on diagnostic tests, collinearity does not appear to be a significant problem, however. The regression analysis employs two data matrices. The first matrix has 284 observations and includes those selling crops, livestock, or both. The second, with 143 observations, is concerned with weather data use for crop production and hence omits producers with no crop sales. Applied researchers consider collinearity degrading if the condition indexes for the data matrix are 30 or more (Belsley et al. 1980; Belsley 1991; Douglass et al. 2003). For the two data matrices, the largest condition indices are 18.5 and 12.6, respectively. Another collinearity diagnostic frequently used is the variance inflation factor (VIF), which measures how much collinearity inflates standard errors of regression estimates. Again, in applied research, VIFs of 10 or higher are considered to indicate collinearity problems [O'Brien (2007) provides discussion and further references]. No variable in either data matrix, however, had a VIF < 3.5.

5. Results and discussion

a. Weather importance index

Table 3 reports results of the negative binomial regressions indexes of weather data use and weather data importance. Controlling for other factors, diversified producers and crop producers tended to find more types of weather data important. Number of commodities sold did not have a significant effect, however. Producers in the three oldest age categories rated more data types important. Rating risk management programs important and having a satellite TV were positively associated with rating more types of data important, while having e-mail access had a negative, but insignificant effect. Owning a greater share of one's farmland had a negative effect. None of the effects of sales class, education, or farm income as a share of total income was significant.

b. Weather data use index

Both crop producers and diversified producers used data for more decisions than did livestock producers (Table 3). Weather data use also increased with the total number of commodities sold. Considering producer personal attributes, being male had no significant impact on data use, nor did having a bachelor's or advanced degree. Being Hispanic, however, was positively associated with data use, as was being in the 45–54 age group. Producers who felt risk management programs were important used data for more decision.

Having e-mail access did not have a significant impact on data use, but having a satellite TV had a positive, significant effect. Producers with greater shares of their household income coming from farming used data for more decisions. This is consistent with previous research suggesting that off-farm work discourages use of management information and technology adoption. Somewhat surprisingly, there was a negative association between both farm sales and percent of farmland owned and data use. Coefficients for the highest and third highest sales class (out of seven classes) were negative and significant.

6. Importance rating of individual types of data

We turn now to importance ratings for individual types of data (Table 4) Table 4 shows coefficients and significance levels only for variables that were at least significant at the 10% level in the probit regressions. Livestock producers were less likely to find temperature, precipitation, soil temperature, frost, and degree-days important than crop producers (the default in these regression). There was no statistically significant difference between crop and diversified producers. Producers in the highest sales class were more likely to find soil temperature and degree-days important. Older producers tended to find more types of data important. Greater farmland ownership had a negative impact on importance ratings for a number of data types, while satellite TV ownership and placing importance on risk-management programs had positive effects. E-mail access had no significant effect on ratings of any of the individual data types.

Applied researchers have developed several different pseudo-R^2 indicators to measure goodness of fit that can be applied to binary choice regressions. However, these often do not have the same interpretation as the R^2 in least squares regression. Here, we employ the adjusted count R^2 (ACR^2) (Long 1997) where

$$\mathrm{ACR}^2 = \frac{\text{Number of observations correctly predicted} - \text{Count of the most frequent outcome}}{\text{Total number of observations} - \text{Count of the most frequent outcome}}. \tag{8}$$

The ACR^2 measures the percent improvement the regression model provides over a ''naïve'' model, which in a binary choice problem, just ''predicts'' that all observations have the most common outcome. For example, if for 60% of the sample, the dependent variable takes on a value of 1 (and 40% of the sample, 0), a naïve model that assumed all observations take on a value of 1, would be correct 60% of the time. Thus, a high proportion of correct predictions does not by itself mean that the model is predicting especially well. The ACR^2 takes on values ranging from 0 (performs no better than always picking the most common response) to 1 (perfect prediction). An ACR^2 = 0.2 suggests the regression model improves on picking the most common response by 20%. The ACR^2 values range from 0.03 for the soil moisture regression to relatively high values (for cross section data) for frost (0.36) and degree days (0.38) (Table 4). Most other values range from 0.16 to 0.26.

a. Weather data use by producer type

The regressions in Table 5 cover agricultural decisions almost exclusively dealing with crop production. Data for these probit regressions only included diversified producers and crop producers, excluding producers with only livestock sales (N = 143). The number of commodities sold increased the probability of using weather data for timing of planting, timing of harvest, and timing cultivation. When coefficients of sales class variables were significant, they tended to be negative and for the higher sales classes. Although greater age was associated with placing importance on more types of weather data, older producers were only more likely to use

TABLE 4. Results from nine probit regressions of weather data importance variables. Dependent variables =1 if a producer rated the data ''important'' or ''most important'' for production and marketing decisions and =0 otherwise. Only statistically significant coefficients are reported. All listed explanatory variables were included in each of the nine regression equations.

	Temperature	Precipitation	Wind speed	Wind direction	Soil moisture	Soil temperature	Frost	Degree days	Relative humidity
Diversified producer (0/1)									
Livestock producer (0/1)	−0.813[a]	−0.604[a]				−0.445[b]	−0.980[a]	−0.479[b]	
Number of commodities sold			0.300[b]						
Avg sales ($10 000–$49 999)									
Avg sales ($50 000–$99 999)									−0.599[c]
Avg sales ($100 000–$249 999)									
Avg sales ($250 000–$499 999)									
Avg sales ($500 000–$999 999)									
Avg sales ($1 000 000 and over)						0.773[c]		0.837[b]	
Age (45–54)			0.571[c]					0.470[c]	0.565[c]
Age (55–64)									0.604[b]
Age (65 and over)		0.610[b]			0.702[b]	0.671[b]	0.618[b]		0.603[b]
Male (0/1)									
Bachelor's degree (0/1)									
Advanced degree (0/1)					0.795[a]				
Farm income/total income (26%–50%)									
Farm income/total income (26%–50%)									
Farm income/total income (76%–100%)									0.519[c]
Hispanic (0/1)							0.563[c]		
Avg land owned >50% (0/1)	−0.437[c]			−0.992[a]	−0.415[c]		−0.443[c]		−0.471[b]
E-mail access (0/1)									
Satellite TV (0/1)	0.495[a]			0.440[c]	0.321[c]			0.405[b]	
Risk management important (0/1)			0.333[c]	0.540[b]				0.525[a]	0.299[c]
Proportion correctly predicted	69.4	63.7	73.6	90.5	68.0	66.2	71.8	72.9	64.4
Adjusted count R^2	0.163	0.202	0.118	0.206	0.032	0.262	0.360	0.384	0.185

[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.

weather data for crop choice. The greater importance older producers placed on data did not translate into using data for decisions. Use of data for several individual decisions was increasing with the share of household income devoted to farming. This suggests that households more reliant on agriculture for their total income have more at stake in adapting to weather conditions. As with the importance regressions, when land ownership was significant it had a negative impact, while the importance rating of risk management programs and satellite TV ownership had positive impacts. E-mail access had no significant effect on use of weather data for individual decisions.

b. *Joint hypothesis tests: Farm and household income diversification*

Finally, we considered joint hypothesis tests for farm income and household income-diversification variables for the probit regressions. These were the following:

- Null hypothesis 1: coefficients for the variables Diversified Producer, Livestock Producer, and Number of Commodities Sold all equal zero (data importance probits);
- Null hypothesis 2: coefficients for Diversified Producer, Livestock Producer, and Number of Commodities Sold, Farm Income/Total Income (26%–50%), Farm Income/Total Income (26%–50%), Farm Income/Total Income (76%–100%), and Ag Land Owned >50% all equal zero (data importance probits);
- Null hypothesis 3: coefficients for Crop Only Producer and Number of Commodities Sold equal zero (weather data use probits); and
- Null hypothesis 4: coefficients for Crop Only Producer, Number of Commodities Sold, Farm Income/Total Income (26%–50%), Farm Income/Total Income (26%–50%), Farm Income/Total Income (76%–100%), and Ag Land Owned >50% all equal zero (data use probits).

TABLE 5. Weather data use probit regressions, crop and diversified producers only. Only statistically significant coefficients are reported. All listed explanatory variables were included in each of the nine regression equations. Dependent variable =1 if producer used weather data for the listed production and marketing decision; =0 otherwise. Producers with no crop sales were excluded from these regressions; 143 observations were included.

	Crop choice	Timing planting	Timing pesticides	Timing harvest	Timing cultivation	Variety choice	Timing irrigation	Crop storage
Crop producer (0/1)					0.675[a]			
Number of commodities sold		0.320[a]		0.328[b]	0.378[b]			
Avg sales (\$10 000–\$49 999)					−1.180[a]	−0.900[a]		
Avg sales (\$50 000–\$99 999)					−1.297[a]			
Avg sales (\$100 000–\$249 999)					−1.519[b]			−1.714[b]
Avg sales (\$250 000–\$499 999)					−1.489[b]	−1.741[b]	−0.918[a]	
Avg sales (\$500 000–\$999 999)					−2.540[c]			−1.961[a]
Avg sales (\$1 000 000 and over)	−1.044[a]				−2.330[c]			−2.140[b]
Age (45–54)	0.902[b]							
Age (55–64)	1.150[b]							
Age (65 and over)	0.782[a]							
Male (0/1)								
Bachelor's degree (0/1)								
Advanced degree (0/1)								
Farm income/total income (26%–50%)		0.913[b]			1.849[c]	0.800[a]		1.522[b]
Farm income/total income (26%–50%)	0.879[a]			0.986[a]	1.536[b]	0.994[a]		1.980[b]
Farm income/total income (76%–100%)	0.904[b]	0.803[a]		0.972[b]	2.258[c]			1.821[b]
Hispanic (0/1)								
Avg land owned >50% (0/1)			−0.840[b]	−0.744[b]				−1.194[b]
E-mail access (0/1)								
Satellite TV (0/1)					0.548[a]			
Risk management important (0/1)			0.497[a]		1.088[c]			
Percent correctly predicted	61.5	68.5	70.6	65.7	75.5	70.6	72.7	90.9
Adjusted count R^2	0.035	0.182	0.373	0.222	0.103	0.035	0.025	0.000

[a] Significant at 10% level.
[b] Significant at 5% level.
[c] Significant at 1% level.

Hypotheses 1 and 3 consider farm income-diversification variables jointly, while 2 and 4 consider household income diversification. We include the landownership variable among the household income variables because Hoppe and Banker (2010) found strong associations between full ownership of agricultural land and low reliance on farm income as a share of total income.

Table 6 shows results of Wald $\chi 2$ tests for the four joint hypotheses for all the probit regressions. The null hypotheses that farm income- or household income-diversification coefficients were jointly insignificant were rejected for most data importance regressions. For the data use regressions, we fail to reject the null that farm income-diversification variables were insignificant in all the regressions. The null of no effect of household income variables could be rejected only for three timing uses (planting, pesticide applications, and harvest).

7. Discussion

The types of weather data farmers and ranchers most frequently found important were data for soil moisture, frost, and temperature. Producers used weather data most frequently for timing of irrigation, followed by livestock management. More specifically, ranchers used weather data frequently for decisions about moving livestock. Next in frequency, producers used weather data for timing of cultivation. There were no other decisions for which more than half of respondents used weather data. The importance of weather data for irrigation timing and frost protection match results of Parker and Zilberman's study of the California Irrigation Management Information System (CIMIS). While they found irrigation scheduling was by far, the primary use of CIMIS information, frost protection was also important.

Consistent with earlier findings, agricultural producer use of weather data varies significantly with commodity

TABLE 6. Joint hypothesis tests on the significance of farm income and household-diversification variables in probit regressions.

	Farm income diversification variables	Household income diversification variables
	Wald χ^2 test P values	
Weather data importance		
Temperature	0.000 29	0.001 46
Precipitation	0.004 69	0.035 00
Wind speed	0.094 32	—*
Wind direction	—	0.055 80
Soil moisture	—	—
Soil temperature	0.001 46	0.016 50
Frost	0.000 00	0.000 02
Degree days	0.000 64	0.007 21
Relative humidity	—	—
Weather data use		
Crop choice	—	—
Crop variety choice	—	—
Timing planting	0.067 80	—
Timing cultivation	0.055 09	0.006 19
Timing pesticides	—	—
Timing irrigation	—	—
Timing harvest	—	0.056 75
Crop storage	—	—

* An em-dash (—) denotes that test fails to reject the null hypothesis (P value > 0.10).

specialization and degree of diversification. Consistent with McNew et al. (1991)'s findings from Oklahoma, crop-only and diversified producers relied on more types of data than did livestock producers. In a study of Ohio farms, Jones et al. (1989) found dairy-only producers were less likely to rate sources of agricultural information useful than were grain-only or diversified producers. McNew et al. (1991) also found that, for decisions involving timing decisions, diversified producers rated weather data more important. In our weather data use regressions, the total number of commodities sold (a measure of diversification) increased the probability of using weather data for timing of planting, harvest, and cultivation. Diversification can reduce risk and possibly decrease demand for risk reducing weather information. However, diversification increases complexity and the need for optimal timing, which can increase demand for information. Our results, and those of McNew et al. (1991) suggest that this complexity/timing effect may be dominant.

The direct effects of greater farm sales on weather data used appeared to be negative in several cases. Regression coefficients for many of the large farm sales categories were negative. This runs counter to theories and past evidence suggesting positive associations between farm size and information/new technology use (e.g., Artikov et al. 2006; Letson et al. 2001). One possible explanation might be that larger operations rely more on hired specialists and consultants. For example, Frisvold and Deva (2011) found that larger operations in Arizona and New Mexico were more likely to use private consultants for water management decisions. Rather than using weather information directly, larger producers may simply be hiring technical consultants, who may be using and interpreting weather data for them.

Access to e-mail had no significant positive effect on the importance producers placed on weather data types or on use of weather data for management decisions. In contrast, access to satellite television had positive effects in several cases. Among survey respondents, 64% of crop producers, 68% of diversified producers, and 59% of livestock producers had e-mail access. However, 38% of all survey respondents did *not* have e-mail access. This suggests that platforms to encourage use of weather information and climate services via web-based tools will not directly reach large segments of Arizona's farmers and ranchers.

One way to interpret the results is that lack of Internet access (as measured by e-mail access) does not appear to be a barrier to weather data use. Those without access do not appear to rate weather data as less important or to use data less for decision making. One reason might be that producers may be receiving weather data indirectly. For example, irrigation district staff, extension agents, etc., may repackage and interpret weather data and information and provide it to producers via print, workshops, or other nonelectronic media. Thus, although producers do not use web-based data *directly*, this data may reach them indirectly, through intermediaries.

Another possible explanation is, however, that producers do not rely on Internet sources of weather data to make production and marketing decisions. McNew et al. (1991) found that television was the primary source of weather information for most producers, ranging from 63%–77% of users depending on type of information. That survey predates the rise of the Internet. Yet, it is notable that, in the Arizona survey, access to satellite television appears to have a more important, positive influence on weather data use than Internet access. This is consistent with findings of Hu et al. (2006) that television rated highly as a factor influencing farmers' weather forecast-use decisions. They found that websites had the lowest influence of any media source.

Turning to farmer personal attributes, having a college or advanced degree did not significantly increase weather data use, although having an advanced degree increased a producer's rating of the importance of soil moisture data. Producers rating government risk-management programs as important also found more weather data types important and used weather data for more decisions. This is consistent with arguments that attitudes toward risk aversion are important considerations in use of data for agricultural decisions (Jones et al. 1989; Just et al. 2002). Women producers and Hispanic producers were not less likely to find weather data important or to use for fewer decisions. In fact, for some decisions, Hispanics were more likely to use weather data.

8. Conclusions

This study made use of questions concerning weather data, included in the Arizona sample of the National Agricultural, Food, and Public Policy Preference Survey, to gain some understanding of weather data use for agricultural decision making. Survey responses from 284 Arizona farmers and ranchers were used to (i) examine the importance producers placed on different types of weather data for production and marketing decisions; (ii) identify which producer characteristics accounted for differences in the importance they placed on weather data; (iii) examine producer use of weather data for specific production and marketing decisions; and (iv) identify which factors distinguish weather data users from nonusers. We conclude by summarizing some general results from multivariate regression analyses and suggest areas for future research.

First, commodity specialization and household income diversification affects use of information. Livestock producers found fewer data types important. Between crop and diversified producers, those producing more, different commodities used weather data for more decisions. Specifically, they were more likely to use data for timing of three activities: planting, cultivation, and harvest. Agricultural diversification can reduce risk and therefore might discourage data use. However, diversification also increases complexity and the value of optimal timing. Our results suggest that these latter effects dominate, increasing demand for weather data. Easterling (1986) found that the timing of weather data was the most important factor for discriminating between weather data users and nonusers.

Nonfarm income, in contrast, discouraged weather data use. Use of weather data increased with the share of household income derived from agriculture. This could result from two effects. First, agricultural income risk is a larger share of household income risk for households engaged primarily in agricultural production. Thus, returns from using data to reduce agricultural risk are greater. Second, producers spending more time in off-farm employment may have less time to process data. Empirical studies of other agricultural decisions have found that off-farm work can discourage information acquisition or use of management time-intensive techniques (Fernandez-Cornejo et al. 2007).

Farms with greater agricultural sales tended to use weather data for fewer decisions, holding all else constant. However, agriculture's share of household income increases with sales volume. As farm sales increase, then, the two effects seem to work in opposite directions. The degree of diversification can also vary with farm sales class. This suggests that further research is needed to sort out the relationships between farm scale, diversification, and off-farm income effects.

Another consistent result was the negative relationship between the percentage of farmland owned and weather data importance and data use. In a comprehensive national study of U.S. farm structure, Hoppe and Banker who found that "retirement farms" and "residential/lifestyle farms" were more likely to be full owners. For these farms, farming is not a significant, let alone primary source of income. For this group, farming can be more of a "lifestyle choice" than moneymaking venture. For this population, intensive use of weather data for farm management may be less of a concern. Producers rating risk management programs important also found more weather data types important and used weather data for more decisions. This is consistent with arguments that risk aversion is an important consideration in use of data for agricultural decisions (Johnson and Holt 1997; Bosch and Eidman 1987).

Finally, Internet access (as measured by e-mail access) did not increase use of data for agricultural decisions or producer assessments of weather data importance. This could mean that other factors, aside from Internet access, are barriers to data use. About 38% of respondents did not have e-mail access. These results raise the question of whether farmers and ranchers get weather data from other sources (e.g., irrigation district staff, cooperative extension, USDA, private consultants) instead of accessing data directly. Alternatively, does it simply mean that few producers rely on web-based weather information sources? Interestingly, access to satellite TV proved to be a much better predictor of positive weather data attitudes and use.

This preliminary study has some obvious limitations. There is only so much information one can glean from just two survey questions about weather data. While our analysis explores the importance of producer heterogeneity, more work is needed to examine heterogeneity of the sources, quality, and technical complexity of the weather data. In addition, more information can be obtained about which types of data are used for which decisions, how and how well producers make use of the data, and *why* producers do not use weather data to make certain decisions. Another possible limitation of this study is that, although we have found some significant associations among variables, this does not necessarily imply causation.

We conclude by mentioning some fruitful areas for future research. First, recent research on demand for economic information for agricultural decision making (e.g., Wolf et al. 2001; Just et al. 2002, 2003) could be usefully applied to demand for meteorological information. Particularly important in this work is the appreciation of multiple sources of heterogeneity (producer/production attributes; data sources; data structure/technical complexity) and its emphasis on the role of intermediaries as processors and translators of information. Two key barriers to use of meteorological information are (i) lack of scientist-information provider knowledge about potential users of that information and (ii) lack of user perceptions of weather information characteristics (Artikov and Lynne 2005).

Second, the work of a University of Nebraska research team brings concepts from behavioral economics and social psychology to bear on farmer information use, using both focus groups and in-depth surveys to sharpen their questions and hypotheses (Artikov et al. 2006; Hu et al. 2006). They found that, in addition to farmer attitudes and financial capacity, social norms and perceived social control also affect farm-level demand for weather information.

Third, work using behavioral specifications of utility (which account for nonmonetary considerations such as environmental stewardship or conforming to social norms, preferences of other household members, or expert recommendations) in combination with economic specifications have proven useful in explaining farm-level adoption of conservation practices (Bishop et al. 2010; Chouinard et al. 2008; Sheeder and Lynne 2011). Our statistical models could only explain a portion of the variation in observed variation in weather use across farmers and ranchers. These other approaches may well prove useful in explaining what we have missed. Further positive, empirical analysis along the lines of these three approaches may substantially improve our understanding how and why agricultural producers use weather information.

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