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Extension Assessments of Farmer Interest in and Uses of Climate Forecasts in Florida, North Carolina, and South Carolina

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EXTENSION ASSESSMENTS OF FARMER INTEREST IN AND USES OF CLIMATE FORECASTS IN FLORIDA, NORTH CAROLINA, AND SOUTH CAROLINA

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ABSTRACT

Farmers can reduce the risks associated with climate variability by using climate forecasts. Extension personnel, as knowledgeable informants about farmers, can assess farmer interest in and uses of climate forecasts in agricultural decision making. Three surveys of extension personnel were conducted in Florida, North Carolina, and South Carolina to assess, among other things, farmer interest in and uses of climate forecasts. Models of conditional probabilities are estimated with data from the surveys to show how extension assessments depend on characteristics of the extensionist and her clientele. An extensionist with more than six years of experience is more likely to think that farmers are interested in using climate forecasts. An extensionist who works with field crop production is more likely to think that a farmer can use climate forecasts to improve planting schedules, land allocation, harvest planning, and crop selection. An extensionist whose average clientele farm size exceeds 200 acres is more likely to indicate that a farmer can use climate forecasts to improve harvest planning, irrigation management, and crop selection. The empirical results provide useful information to those interested in expanding the adoption of climate forecasts in Florida, North Carolina, and South Carolina.

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INTRODUCTION

Climate is a long-term synthesis of weather conditions in an area and varies from year-to-year (Breuer et al. 2008, p. 385). A major influence on inter-annual climate variations in the southeast U.S. and other regions is the El Niño-Southern Oscillation (ENSO) and its associated phases, El Niño, neutral, and La Niña (Cane 2000; Fraisse et al. 2006, p. 15). For example, El Niño winters have lower winter temperatures than La Niña or neutral winters in the region, as well as higher precipitation in Gulf Coast states (Jones et al. 2000, p. 171). El Niño springs have higher rainfall in the entire southeastern U.S. but lower rainfall along the Atlantic Coast and from north Texas to northern Alabama during the summer (Jones et al. 2000, p. 171). These seasonal differences include rainfall that can vary by as much as 30 percent from average and temperatures that are 2 to 3° C above or below average (Breuer et al. 2008, p. 386).

Climate variability creates production risks for farmers in the Southeast U.S. For example, ENSO phases significantly influence yield distributions of corn, cotton, and peanuts in most counties of south-central Georgia, south-central Alabama, northern Alabama, and northwestern Florida (Nadolnyak et al. 2008, p.1250-1251). Southern winds and low temperatures in Alabama and Georgia during July-September are significantly correlated with and statistically explain as much as 52 percent of the inter-annual variability in observed yields of cotton in the two states (Baigorria et al. 2008, pp. 76 and 81-82).

The economic impact of climate variability can be substantial in the region. For example, "ENSO phases significantly influenced…farm-gate revenues of corn, soybean, peanuts, and tobacco during 1960-1995 in Alabama, Florida, Georgia, and South Carolina," (Hansen et al. 1998, p. 404). During a prolonged drought in the 1980s, up to one-third of full-time family farms in a central Georgia county were forced out of business (Crane et al. 2010, p. 50). In 2007, freeze contributed to farm-gate revenue losses of $105 million in North Carolina and $39.3 million in South Carolina (NOAA-USDA 2008). Furthermore, federal crop insurance has paid an average of $117.8 million per year for losses caused by drought, $47 million per year for losses caused by excess precipitation and moisture, and $30.9 million per year for losses caused by freeze in Florida, North Carolina, and South Carolina between 2008 and 2012 (RMA 2012).

Farmers have access to various technologies, institutions, and social networks—such as irrigation, crop insurance, and extension—to respond to climate variability (Crane et al. 2010, p. 46). For example, extension personnel can provide and interpret climate information to assist farmers in making production decisions (Mase and Prokopy 2013, pp. 59-60). The agricultural training and experience of extension personnel make them sources of information about attitudes of farmers towards climate information and the potential adopting by farmers of decision support tools based on climate information. However, farmer interest in and possible uses of climate information, as assessed by extension personnel, has received limited attention in the literature (Mase and Prokopy 2013, p. 49). The goal of this study is to expand this literature. In particular, my research has the following objectives:

1) To determine the effects of characteristics of an extensionist and his clientele on the probability that he indicates farmers are interested in using climate forecasts.

2) To determine the effects of characteristics of an extensionist and his clientele on the probability that he indicates that farmers could improve a particular managerial activity through the use of climate forecasts.
3) To determine the effects of characteristics of an extensionist and his clientele on the probability that he indicates that a farmer who engages in a particular type of agricultural production is likely to be able to use climate forecasts to be more successful.

The data from responses to three similar surveys of extension personnel have been analyzed in previous research. However, neither the substance nor the methods of previous research enable one to address these research objectives. In particular, statistical tests were conducted for differences in the mean willingness of extension personnel at North Carolina State University and University of Florida to provide advice about climate forecasts conditional on the agent's age and gender, work region, or clientele's farm size (Breuer et al. 2011; Cabrera et al. 2006). It was shown that the mean response of 36 to 55 year old females in North Carolina were significantly different from the other category means (Breuer et al. 2011). Furthermore, 86.5 percent of surveyed extension agents at UF (Cabrera et al. 2006) and 65.1 percent of extension agents surveyed at NCSU (Breuer et al. 2011) indicated that agricultural producers are interested in using climate forecasts. The data collected from extension personnel at Clemson University and the probability distributions of binomial random variables were used to test whether a majority of extension personnel at the university share opinions about the usefulness and uses of climate forecasts (Templeton et al. 2013). These data were also used to "test for differences in proportions of Clemson's extension personnel who select which forecasts are useful or which managerial activities their clientele could improve with a climate forecast," (Templeton et al. 2013). 71 percent of the extension personnel surveyed in South Carolina agree or strongly agree that growers in producers in their region are interested in using climate forecasts. Additionally, it was found that farmers are likely to use climate forecasts to improve land allocation, crop selection, irrigation management, and planting schedules (Templeton et al. 2013).

In this paper, models of conditional probabilities are estimated to show how extension assessments of farmer interest in and uses of climate forecasts change based on characteristics of the extensionist and her clientele. The results these models, considered together, indicate that those interested in expanding the use of climate forecasts in agriculture should utilize the knowledge of extension personnel with relatively more experience in general or more experience about specific types of agricultural production. The econometric models are derived from a conceptual model of how the benefits and costs to farmers of using climate forecasts influence the assessments made by extension personnel.

BENEFITS AND COSTS TO FARMERS OF USING CLIMATE FORECASTS: AN EXTENSIONISTS PERSPECTIVE

When making assessments of farmer interest in and uses of climate forecasts, extension personnel account for, by assumption, the benefits and costs to farmers who would use climate information. A climate forecast can be beneficial to a farmer's decision making if the farmer is able to reduce risks, improve yield, or decrease production costs, by changing his or her actions based on the information provided by the forecast. One type of cost of using a climate forecast is the time and effort needed to access, understand, and interpret the forecast (Murphy 1993, p. 286). The benefits and costs of a forecast depend, in turn, on the type of decision that a farmer makes, characteristics of the crop(s) and of the farm for which the decision is made, and characteristics of the farmer (Crane et al. 2010; Mase and Prokopy 2013).

The costs and benefits to farmers of using climate forecasts, as assessed by extension personnel, may also depend on characteristics of the personnel themselves. The costs and benefits may also depend on the state in which the extensionist works, as different states experience different climate conditions. The appointment and associated job description of an extensionist's position may also influence his assessments. Extension agents are typically more involved with advising farmers than extension associates or specialists and may have a better idea of the costs and benefits of using climate forecasts.

When making an assessment, extension personnel also consider their knowledge and experience working with farmers. Extension personnel who work with a particular type of crop production are presumably more knowledgeable of the costs and benefits of altering that type of production system. As such, these personnel can provide a better-informed assessment of whether related managerial activities could be improved or if that type of production can be made more successful by using climate forecasts. Additionally, more experienced extension personnel may have a broader knowledge base. As such, they may have a better understanding of the economic impact of a particular change in production decisions or of farmer sentiments about climate forecasts.

The potential costs and benefits of using climate information may depend on the size of a farmer's operation. The cost of utilizing climate information is quasi-fixed because climate forecasts are employed in a fixed amount for any positive level of output. If the use of climate information improves the management of agricultural activities, then the benefit of the information will increase with the scale of production. As a result, farmers with larger operations may be more likely to use the information than farmers with smaller operations (Breuer et al. 2008 p. 395) because the expected benefits of using the forecasts will at some farm size begin to exceed the quasi-fixed costs.

DATA SOURCES AND VARIABLES

The data for this study were organized and combined from three data sets. Relevant data in each set come from responses to identical or almost identical portions of three surveys. The original survey was conducted in November and December of 2004 by researchers with the Southeast Climate Consortium among agricultural extension agents at University of Florida (Cabrera et al 2006). This survey received 89 responses from a population of 166 extension agents. A similar survey was conducted in March and April of 2009 by SECC researchers among extension agents at North Carolina State University (Breuer et al 2011). This survey received 109 responses from an unknown population of extension agents. A third survey was conducted in January and February of 2011 among extension agents, associates, and specialists at Clemson University. This survey received 49 responses from a population of 171 extension agents, associates, and specialists. Of the 247 responses, approximately 19 percent of responses were not usable because not all respondents completed the survey.

Categorical responses to two statements and a question in the surveys are the sources of data for dependent variables. The first statement is, “In my opinion, growers and producers (including forest owners, livestock producers, etc.) in my region are interested in using climate forecasts. 1) strongly agree, 2) agree, 3) neither agree nor disagree, 4) disagree, or 5) strongly disagree.” Let $Y_r = 1$ if respondent r selects ‘strongly agree’ or ‘agree’ and 0 if not and let $Y \equiv \sum_{r=1}^{202} Y_r$ be the number of respondents, $r= 1, 2,\ldots,202$, who select ‘strongly agree’ or ‘agree’. Seven of ten survey respondents strongly agree or agree that farmers are interested in using climate forecasts (Table 1).

The second statement is, “People I work with can use climate forecasts to improve … (Check all that apply)”. The managerial activities that might be improved with climate forecasts are these: 1) planting schedules, 2) allocation of land to crops or activities, 3) labor management, 4) harvest planning, 5) waste management, 6) nutrient management, 7) irrigation management, 8) marketing, 9) variety or crop selection, 10) spacing or stand density, and 11) other. In the South Carolina and North Carolina surveys, ‘integrated pest management’ was also an option. Selections of this option were re-categorized for this analysis as selections of ‘other’ to enable comparisons with data from the Florida survey. Let $I_{r,a}= 1$ if respondent r checks managerial activity a and 0 if not and let $I_a \equiv \sum_{r=1}^{199} I_{r,a}$ be the number of respondents, $r = 1, 2,\ldots,199$, who check activity a. Planting schedules was the most frequently selected managerial activity (Table 1).

The question is “Who is likely to be able to use climate forecasts to be more successful? (Check all that apply)…" The types of users were these: 1) row crop farmers, 2) vegetable farmers, 3) nursery operators, 4) orchard growers, 5) livestock (cattle, hog, poultry, etc.) producers, 6) emergency planners, 7) water resource managers, 8) aquaculture producers, 9) extension agents, 10) forest managers/owners, 11) tourism industries, 12) landscapers, and 13) other. Let $S_{r,f} = 1$ if respondent *r* indicates type of farmer *f* and 0 if not and let $S_f = \sum_{r=1}^{200} S_{r,f}$ be the number of respondents, *r* = 1, 2,…,200, who indicate type of farmer *f*. Vegetable producers were the most frequently selected type of user (Table 1).

Categorical responses to several questions about the characteristics of the respondent and his or her clientele are the sources of data for independent variables. Eighty percent of all respondents were male and half of all respondents worked for North Carolina State University (Table 2). Most respondents were extension agents, while a minority of respondents from South Carolina was extension associates or specialists. Three-fourths of the respondents were over 45 years old and 60 percent of respondents had more than six years of experience in extension. 64 percent of respondents worked with farmers who had an average farm size less than 200 acres. Field- and vegetable crops are more likely to be relevant to the respondent's work, i.e. the extensionist works with farmers who produce field- and vegetable-crops, compared to livestock and fruit production (Table 2).

ECONOMETRIC MODEL

Let X_r' be a vector of dummy variables that represent fifteen characteristics of respondent *r* and his or her clientele. $\boldsymbol{\beta}$, $\boldsymbol{\gamma}_a$, and $\boldsymbol{\lambda}_f$ are vectors of the assumed parametric effects that the characteristics have on the three probabilities considered in this study. In the researcher's mind, the logit probability that respondent *r* indicates that farmers are interested in using climate forecasts is

$$P_{Y_r} \equiv P(Y_r = 1) = \frac{\exp(X_r'\boldsymbol{\beta})}{1+\exp(X_r'\boldsymbol{\beta})} \quad (1.1).$$

The logit probability that respondent *r* indicates that the people with whom he or she works could use climate forecasts to improve agricultural activity *a* is

$$P_{I_{r,a}} \equiv P(I_{r,a} = 1) = \frac{\exp(X_r'\boldsymbol{\gamma}_a)}{1+\exp(X_r'\boldsymbol{\gamma}_a)} \quad (2.1).$$

The probability that respondent r indicates that type of farmer *f* is likely to be able to use climate forecasts to be more successful is

$$P_{S_{r,f}} \equiv P(S_{r,f} = 1) = \frac{\exp(X_r'\boldsymbol{\lambda}_f)}{1+\exp(X_r'\boldsymbol{\lambda}_f)} \quad (3.1).$$

The unconstrained likelihood functions are

$$L_Y = \prod_{r=1}^{R} (P_{Y_r})^{Y_r} (1-P_{Y_r})^{1-Y_r} \qquad (1.2)$$

where Y_r = 1 if respondent *r* indicates farmers are interested in using climate forecasts and 0 if not,

$$L_{I_a} = \prod_{r=1}^{R} (P_{I_{r,a}})^{I_{r,a}} (1-P_{I_{r,a}})^{1-I_{r,a}}, \qquad (2.2)$$

where $I_{r,a}$ = 1 if respondent *r* indicates that the people he or she works with could use climate forecasts to improve activity *a* and 0 if not, and

$$L_{S_f} = \prod_{r=1}^{R} (P_{r,f})^{S_{r,f}} (1 - P_{r,f})^{1-S_{r,f}}, \qquad (3.2)$$

where $S_{r,f} = 1$ if respondent *r* indicates that type of farmer *f* is likely to be able to use climate forecasts to be more successful and 0 if not.

The vectors $\boldsymbol{\beta}$, $\boldsymbol{\gamma}_a$, and $\boldsymbol{\lambda}_f$ were estimated by the Newton-Raphson algorithm in the LOGIT procedure of STATA Version 10.1 to maximize L_Y, L_{I_a}, and L_{S_f}, respectively, and obtain $\hat{P}_r$, $\hat{P}_{r,a}$, and $\hat{P}_{r,f}$ (StataCorp). The estimators, $\hat{\boldsymbol{\beta}}$, $\hat{\boldsymbol{\gamma}}_a$, and $\hat{\boldsymbol{\lambda}}_f$, are consistent, asymptotically efficient, and asymptotically normally distributed (Templeton et al. 2010, p. 61).

The discrete effect of the k^th indicator variable on the estimated probability that respondent *r* indicates that farmers are interested in using climate forecasts is

$$\hat{P}_{Y_r}^{k} - \hat{P}_{Y_r}^{\sim k} = \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} + \hat{\beta}_k)}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} + \hat{\beta}_k)} - \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})} \ (1.3).$$

The discrete effect of the k^th indicator variable on the estimated probability that respondent *r* indicates that the people he or she works with could use climate forecasts to improve activity *a* is

$$\hat{P}_{I_{r,a}}^{k} - \hat{P}_{I_{r,a}}^{\sim k} = \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\gamma}}_a^{\sim k} + \hat{\gamma}_a^{k})}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\gamma}}_a^{\sim k} + \hat{\gamma}_a^{k})} - \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\gamma}}_a^{\sim k})}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\gamma}}_a^{\sim k})} \ (2.4).$$

The discrete effect of the k^th indicator variable on the estimated probability that respondent *r* indicates that type of farmer *f* is likely to be able to use climate forecasts to be more successful is

$$\hat{P}^{k}_{S_{r,f}} - \hat{P}^{\sim k}_{S_{r,f}} = \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\lambda}}_f^{\sim k} + \hat{\lambda}_f^{k})}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\lambda}}_f^{\sim k} + \hat{\lambda}_f^{k})} - \frac{\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\lambda}}_f^{\sim k})}{1+\exp(\boldsymbol{X}_r'^{\sim k}\hat{\boldsymbol{\lambda}}_f^{\sim k})} \quad (3.4).$$

$\hat{X}_r^{\sim k}$ is a vector of variables representing all but the k[th] characteristic of respondent *r* or his clientele. $\hat{\boldsymbol{\beta}}^{\sim k}$ is a vector of coefficient estimates for all but the coefficient estimate for the k[th] characteristic in the first model. $\hat{\boldsymbol{\gamma}}_a^{\sim k}$ and $\hat{\boldsymbol{\lambda}}_f^{\sim k}$ are defined similarly.

RESULTS

Are Farmers Interested in Using Climate Forecasts?

Parameter estimates, standard errors, z-statistics, and *p*-values for variables in the logit model of the probability that an extension agent indicates farmers are interested in using climate forecasts are presented in Table 3.1. Several characteristics of extension personnel, namely gender, age, and the size of his or her own farm, do not significantly influence this probability. However, the extension personnel's experience and state of employment statistically matter (Table 3.1). The probability that an extensionist indicates that farmers are interested in using climate forecasts is 17.8 percentage points higher, on average, if the extensionist has more than six years of experience in extension (Table 3.2). Extension personnel who work with vegetable production and forage or beef production are less likely to indicate that farmers are interested in using climate forecasts. This probability decreases 15.4 percentage points, on average, if vegetable production is relevant to the extensionist's work and by 13.8 percentage points, on average, if forage or beef production is relevant to the extensionist's work (Table 3.2).

Which Management Activities Could Farmers Improve Using Climate Forecasts?

Parameter estimates and robust standard errors for variables in the logit model of the probability that an extensionist indicates that farmers could use climate forecasts to improve several agricultural activities are presented in Table 4.1. I do not include labor, waste, and nutrient management in Table 4.1 because I do not find a significant relationship between these activities and any of the characteristics of the extensionist and his or her clientele. Spacing or stand density is not included because it is not related to traditional agricultural production.

If an extensionist manages at least two acres, the probability that he or she indicates that farmers could improve land allocation and crop selection using climate forecasts increases. In particular, if an extensionist manages a farm with greater than two acres, the probability that the extensionist indicates that land allocation could be improved using climate forecast increases 15.3 percentage points, on average, while the probability that crop selection could be improved using climate forecasts increases, on average, 20.1 percentage points (Table 4.2).

Extensionists who work with field crop production are more likely to think that several managerial activities could be improved using climate forecasts (Table 4.1). For instance, the probability that the extensionist indicates that farmers could use climate forecasts to improve plant scheduling increases 12.4 percentage points, on average, if field crop production is relevant to an extensionist’s work (Table 4.2). If field crop production is relevant to an extensionist’s work, the probabilities that the extensionist indicates that farmers could improve harvest planning and crop selection increases 10.2 and 18.3 percentage points, respectively. Furthermore, the probability that an extensionist indicates that land allocation could be improved using climate forecasts increases by 21.9 percentage points, on average, if the extensionist works with field crop production (Table 4.2).

The probability that an extensionist indicates that land allocation can be improved using climate forecasts increases, on average, 16.5 percentage points if beef cattle or forage production are relevant to the extensionist's work (Table 4.2). The probability that an extensionist indicates that planting schedules and irrigation management could be improved using climate forecasts increases, on average, by 11.8 and 14.7 percentage points, respectively, if the extensionist works with greenhouse and nursery production. Additionally, the probability that an extensionist indicates that planting schedules could be improved decreases, on average, by 15.6 percentage points if the extensionist works with perennial fruit production (Table 4.2).

The probability that an extensionist indicates that farmers can use climate forecasts to improve harvest planning increases, on average, 14.3 percentage points if the average farm size of his or her clientele is greater than 200 acres. The probability that crop selection could be improved using climate forecasts increases 16.4 percentage points, on average, if the average clientele farm size exceeds 200 acres (Table 4.2). The probability that extension personnel indicate that farmers can use climate forecasts to improve irrigation increases 14.8 percentage points, on average if the average clientele farm size is greater than 200 acres.

Which Types of Farmers Are Likely to Be Able to Use Climate Forecasts to be Successful?

Parameter estimates and robust standard errors for variables in the logit model of the probability that an extensionist indicates that several types of farmers are likely to be able to use climate forecasts to be more successful are reported in Table 5.1. I do not include emergency planners, water resource managers, extension agents, tourism industries, and landscapers in Table 5.1 because these groups are not agricultural producers. Aquaculture producers and forest managers/owners are not included because they are not considered to be traditional agricultural producers.

In general, the probability that an extensionist indicates that a farmer who engages in a particular type of production is likely to be able to use climate forecasts to be more successful increases if the extensionist works with that type of production. In particular, the probability that an extensionist indicates that row crop farmers are likely to be able to use climate forecasts to be more successful increases 28.3 percentage points, on average, if field crop production is relevant to the extensionist's work (Table 5.2). The probability that vegetable producers are likely to be able to use climate forecasts to be successful increases, on average, 11 percentage points if vegetable crop production is relevant to the extensionist's work, while the probability for orchard growers increases 24 percentage points, on average, if the extensionist works with perennial fruit production. The probability that extension personnel indicate that livestock managers are likely to be able to use climate forecasts to be more successful increases 26.2 percentage points, on average, if beef cattle or forage production are relevant to the extensionist's work (Table 5.2). This holds true for nursery producers as well, as this probability increases 31.4 percentage points, on average, if greenhouse and nursery production is relevant to the extensionist. However, the probabilities that an extensionist indicates that livestock producers and nursery operators are likely to be able to use climate forecasts to be more successful decrease, on average, by 26.5 and 17.6 percentage points, respectively, if the extensionist works with vegetable production. Additionally, the probability that an extensionist indicates that row crop farmers are likely to be able to use climate forecasts to be more successful decreases by 14.4 percentage points, on average, if nursery production is relevant to the extensionist's work (Table 5.2).

DISCUSSION

The results are consistent with several factors discussed in the conceptual model. For example, an extensionist who works with farmers with larger operations is more likely to indicate that harvest planning, crop selection, and irrigation management can be improved using climate farmers. As such, farmers with large operations may have greater uses for climate forecasts than farmers with small operations (Breuer et al. 2008, p. 395) because the expected benefits of using the forecasts exceed the quasi-fixed costs of using them at some farm size. An extensionist who works with farmers with larger operations is neither more nor less likely to indicate that planting schedules and land allocation could be improved using climate forecasts. This may be because planting schedules and rotations are on a rigid schedule on larger farms, making it more difficult to alter the schedule based on climate predictions (Breuer et al. 2008, p. 395). An alternative explanation for these results is that extensionists who work with clientele with large farms may be more likely to think their clientele are interested in using climate forecasts because the extensionist's productivity would be higher or the cost of relaying the information lower if he or she works with farmers who have large operations. Clientele farm size did not have a significant effect on the probability that extension personnel indicate that a particular type of farmer is likely to be able to use climate forecasts to be more successful. One possible interpretation of this result is that regardless of the type of production that takes place on a farm, larger farms are more likely to benefit in aggregate from using climate forecasts.

Extensionists who work with field crop production are more likely to think a farmer could use a climate forecast to improve planting schedules, harvest planning, crop selection, and land allocation is consistent with findings from several informal meetings with farmers and extension agents. For example, production practices for some row crops, such as corn, soybeans, and peanuts, show potential for adaptation (Crane et al. 2010, pp. 54-55). Farmers could decide not to plant corn and soybeans if dry weather is expected (Hildebrand et al. 1999, p. 5), while farmers could alter peanut planting dates based on climate forecasts (Hildebrand et al. 1999, p. 11). Row crop farmers could also plant more drought- and heat-tolerant crops given climate predictions (Crane et al. 2010, p. 54). In an interview, one peanut farmer mentioned how he could change where he planted his crop depending on seasonal climate predictions (Crane et al. 2011, p. 183).

Although extension personnel for whom vegetable production was relevant to their work are more likely to indicate that vegetable producers are likely to be able to use climate forecasts to be successful, they are less likely to indicate farmers are interested in using climate forecasts. One interpretation for this seemingly anomalous result comes from informal meetings with farmers and extension agents. Vegetable producers could be more successful by planting more if wet weather is expected over the summer and planting less or none if dry conditions are expected (Hildebrand et al. 1999, p. 5).

Vegetable producers could also be more successful by adapting irrigation strategies based on wet and dry season predictions (Hildebrand et al. 1999, p. 11) or changing crops and timing in response to climate predictions (Hildebrand et al. 1999, p. 13). Furthermore, since the price of vegetables is greatly affected by production in competing regions, vegetable producers could use climate predictions in these regions to determine what and how much to plant (Hildebrand et al. 1999, p.14). However, "…extension agents expressed reservations about the applicability of climate forecasts in this industry. They argued instead that there is a need to address vegetable marketing and to cover costs related to infrastructure, rather than predicting climate," (Hildebrand et al. 1999, p. 11). This argument may explain why other research finds a low potential for the adoption of climate forecasts in vegetable production (Breuer et al. 2008, p. 393). In short, other concerns may limit the interest that vegetable farmers have in using climate forecasts even though, if they did adopt, vegetable farmers could use the forecasts to be more successful.

If a particular type of agricultural production is relevant to an extensionist's work, why is the extensionist more likely to think that a farmer who engages in that type of production can probably use climate forecasts to be more successful? Extension personnel who work with a particular type of crop production are more knowledgeable of the costs and benefits of altering that type of production system, and thus can provide a better-informed assessment of whether that type of production can be more successful using climate forecasts. However, I do not have an explanation as to why extension personnel who work with vegetable production are less likely to indicate that livestock managers and nursery operators are likely to be able to use climate forecasts to be more successful.

An extensionist's experience only influences the probability that extensionists indicate that farmers are interested in using climate forecasts. An explanation for this result is that more experienced extensionists may have a better defined extension program than their less experienced counterparts. As such, they may be in a better position to add relatively new information, such as climate forecasts, to their program. Although more experienced extensionists may be more interested in extending climate information to farmers, they may not know much about the type of managerial activities or the type of farmers that could benefit from the use of climate forecasts.

CONCLUDING REMARKS

The models of the assessments made by extension personnel about the potential uses of climate forecasts presented in this paper simplify the reality of the agricultural decision-making process. Even so, the empirical results of the conditional probabilities of extension assessments are consistent with findings from informal meetings with extension agents and farmers, as well as several factors discussed in the conceptual model. However, empirical measurement of the conditional probabilities of *farmer* assessments of the potential uses of climate forecasts is important for future research. Attention must also be given to possible differences between stated and revealed preferences for climate forecasts, so future research should also study the extent to which farmers actually use climate forecasts in production decisions.

This study is limited by the scope and nature of the data available. I do not have data measuring the age, gender, and farming experience of the extensionist's clientele. Information on the specific crops, not just types of crops, relevant to the extensionist's work may also provide a more refined assessment of the potential uses of climate forecasts. Additionally, I was unable to measure forecast accuracy and timing, two qualities that greatly influence the potential costs and benefits of using climate forecasts (Murphy 1993). Since the surveys conducted in each state occurred in different years, the state variables included in these models are difficult to interpret because they capture the effect of both state and year on the extensionist's assessment. Lastly, these results may be influenced by some inherent difference between respondents and non-respondents, as respondents may have been more enthusiastic about forecasts than non-respondents (Templeton et al. 2013).

Nonetheless, my results provide useful information about the potential uses of climate forecasts to those interested in expanding the adoption of climate forecasts in Florida, North Carolina, and South Carolina. Although I am unaware of the extent that climate forecasts are currently used in these states, these results can be used to better target particular types of farms and agricultural activities in order to improve adoption. Those interested in expanding the adoption of climate forecasts may be able to do so by targeting the improvement of particular managerial activities on larger farms, although my results indicate that these individuals should consult with extension personnel who are more familiar with that type of production. The greatest potential for adoption appears to be in field crop production, as extension personnel who work with field crop production are more likely to think several managerial activities relevant to this type of production can be improved by climate forecasts.

Table 1. Descriptive Statistics of Dependent Variables

Indicator Variable	Observations	Sample Proportion
Farmer Interest (= 1 if the respondent agrees or strongly agrees that farmers are interested in using climate forecasts)	202	.713
Planting Sched. (= 1 if the respondent indicates planting schedules could be improved by using climate forecasts)	199	.794
Irrigation Mgt. (= 1 if the respondent indicates irrigation management could be improved by using climate forecasts)	199	.668
Harvest Planning (= 1 if the respondent indicates harvest planning could be improved by using climate forecasts)	199	.653
Crop Selection (= 1 if the respondent indicates variety or crop selection could be improved by using climate forecasts)	199	.608
Land Alloc. (= 1 if the respondent indicates land allocation could be improved by using climate forecasts)	199	.543
Vegetable Farmers (= 1 if the respondent indicates vegetable farmers are likely to be more successful using climate forecasts)	200	.840
Row Crop Farmers (= 1 if the respondent indicates row crop farmers are likely to be more successful using climate forecasts)	200	.760
Orchard Growers (= 1 if the respondent indicates that orchard growers are likely to be more successful using climate forecasts)	200	.635
Nursery Operators (= 1 if the respondent indicates nursery operators are likely to be more successful using climate forecasts)	200	.605
Livestock Producers (= 1 if the respondent indicates livestock producers are likely to be more successful using climate forecasts)	200	.590

Table 2. Descriptive Statistics (n = 202) of Independent Variables

Variable	Mean
SCAROLINA (= 1 if the respondent is from South Carolina)	.203
NCAROLINA (= 1 if the respondent is from North Carolina)	.500
FLORIDA (= 1 if the respondent is from Florida)	.297
MALE (= 1 if the respondent is male)	.802
SCNONAGENT (= 1 if respondent is an extension associate or specialist)	.094
OVER45AGE (= 1 if the respondent is older than 45 years old)	.604
BIGCLIENTFARM (= 1 if the average farm size of the respondent's clientele is more than 200 acres)	.361
NOTSMALLOWNFARM (= 1 if the respondent manages more than 2 acres of land for agricultural production)	.396
OVER6EXPER (= 1 if the respondent has more than 6 years of experience in extension)	.733
FIELDCROP (= 1 if field crop production is relevant to the respondent's work)	.441
VEGCROP (= 1 if vegetable production is relevant to the respondent's work)	.406
FORAGEBEEF(= 1 if beef cattle or forage production are relevant to the respondent's work)	.391
NURSERYGH (= 1 if greenhouse and nursery production is relevant to the respondent's work)	.371
PERENNIALFRT (= 1 if perennial fruit production is relevant to the respondent's work)	.347

Table 3.1. Logit model of the probability that an extensionist indicates growers and producers are interested in using climate forecasts

Number of Obs. = 202

Variable	Parameter Estimate	Standard Error	z statistic	Two-sided p value
CONSTANT	1.967	.775	2.54	.011
SCAROLINA	-1.489	.880	-1.69	.091
NCAROLINA	-3.114	.690	-4.52	.000
MALE	.080	.503	.16	.874
SCNONAGENT	-1.454	.823	-1.77	.077
OVER45AGE	.399	.469	0.85	.394
BIGCLIENTFARM	.783	.501	1.56	.118
NOTSMALLOWNFARM	.365	.414	.88	.377
OVER6EXPER	1.160	.501	2.31	.021
FIELDCROP	.523	.481	1.09	.276
VEGCROP	-1.086	.518	-2.10	.036
FORAGEBEEF	-.947	.433	-2.19	.029
NURSERYGH	.586	.471	1.24	.214
PERENNIALFRT	.768	.549	1.40	.162

Table 3.2. Discrete effects from the model of the probability that an extensionist indicates growers and producers are interested in using climate forecasts

Number of Obs = 202

Variable	$\hat{P}_{Y_r}^{k}$	$\hat{P}_{Y_r}^{\sim k}$	$\hat{P}_{Y_r}^{k} - \hat{P}_{Y_r}^{\sim k}$
OVER6EXPER	.765	.587	.178
VEGCROP	.619	.772	-.154
FORAGEBEEF	.626	.764	-.138

Table 4.1. Logit model of the probability that an extensionist indicates climate forecasts can be used to improve a particular managerial activity

Number of Obs = 199

Variable	Planting Sched.	Harvest Planning	Crop Selection	Land Alloc.	Irrigation Mgt.
CONSTANT	1.601** (.696)	.334 (.536)	-.586 (.538)	-1.596*** (.557)	.819 (.557)
SCAROLINA	-.438 (.657)	.608 (.618)	.593 (.618)	.539 (.607)	.035 (.629)
NCAROLINA	.111 (.491)	-.008 (.388)	.048 (.389)	.547 (.398)	-.771* (.408)
MALE	-.388 (.549)	.069 (.430)	-.174 (.427)	-.186 .422	-.241 (.430)
SCNONAGENT	-1.474* (.777)	-1.300* (.766)	-1.631** (.791)	-.241 (.750)	-.427 (.741)
OVER45AGE	-.763 (.539)	-.686 (.438)	-.092 (.437)	-.287 (.434)	-.572 (.413)
BIGCLIENTFARM	.690 (.497)	.730* (.399)	.832** (.398)	.232 (.383)	.751* (.401)
NOTSMALLOWNFARM	.205 (.441)	.270 (.359)	1.014*** (.005)	.745** (.346)	.089 (.347)
OVER6EXPER	.247 (.579)	-.029 (.474)	-.058 (.473)	.685 (.463)	.163 (.454)
FIELDCROP	.939* (.508)	1.036** (.405)	.897** (.399)	1.018*** (.391)	-.125 (.399)
VEGCROP	.271 (.501)	-.005 (.417)	.026 (.417)	.218 (.416)	.687 (.429)
FORAGEBEEF	-.016 (.469)	.011 (.378)	.160 (.376)	.802** (.365)	.400 (.373)
NURSERYGH	.906* (.475)	.257 (.380)	.500 (.389)	-.008 (.388)	.743* (.391)
PERENNIALFRT	-1.085** (.502)	-.384 (.408)	.044 (.409)	.136 (.414)	-.475 (.427)

*** $p \leq .01$;** $p \leq .05$; * $p \leq .10$

Table 4.2. Discrete effects from the model of the probability that an extensionist indicates climate forecasts can be used to improve a particular managerial activity

Number of Obs = 199

Model	Variable	$\hat{P}^{k}_{I_{r,a}}$	$\hat{P}^{\sim k}_{I_{r,a}}$	$\hat{P}^{k}_{I_{r,a}} - \hat{P}^{\sim k}_{I_{r,a}}$
Planting Schedules	FIELDCROP	.867	.743	.124
	NURSERYGH	.863	.745	.118
	PERENNIALFRT	.686	.842	-.156
Land Allocation	NOTSMALLOWNFARM	.637	.484	.153
	FIELDCROP	.667	.448	.219
	FORAGEBEEF	.644	.479	.165
Harvest Planning	BIGCLIENTFARM	.749	.606	.143
	FIELDCROP	.667	.565	.102
Irrigation Management	BIGCLIENTFARM	.761	.613	.148
	NURSERYGH	.759	.612	.147
Crop Selection	BIGCLIENTFARM	.716	.552	.164
	NOTSMALLOWNFARM	.732	.531	.201
	FIELDCROP	.715	.532	.183

Table 5.1. Logit model of the probability that an extensionist indicates a particular type of farmer is likely to be able to use climate forecasts to be more successful

Number of Obs = 200

Variable	Row Crop Farmers	Vegetable Farmers	Livestock Managers	Nursery Operators	Orchard Growers
CONSTANT	.917 (.610)	1.545** (.689)	-.141 (.535)	.815 (.560)	.309 (.525)
SCAROLINA	.917 (.689)	-.563 (.717)	.679 (.596)	-.982* (.586)	.217 (.587)
NCAROLINA	.882* (.456)	-.131 (.519)	.057 (.394)	-1.074** (.423)	-.252 (.388)
MALE	-.247 (.508)	-.038 (.531)	-.191 (.433)	.666 (.427)	.410 (.419)
SCNONAGENT	-1.004 (.818)	.032 (.817)	-1.350* (.730)	-.311 (.699)	.393 (.747)
OVER45AGE	-.098 (.519)	.474 (.498)	.190 (.424)	.388 (.416)	.439 (.416)
BIGCLIENTFARM	-.320 (.494)	.128 (.513)	.048 (.389)	.207 (.376)	.105 (.377)
NOTSMALLOWNFARM	-.254 (.429)	.020 (.452)	.208 (.349)	-.251 (.342)	-.064 (.342)
OVER6EXPER	-.071 (.556)	-.689 (.594)	.431 (.457)	-.424 (.462)	-.457 (.466)
FIELDCROP	2.023*** (.569)	.604 (.520)	.164 (.408)	-.053 (.387)	-.521 (.394)
VEGCROP	-.688 (.466)	.960* (.583)	- 1.289*** (.424)	-.911** (.441)	-.339 (.421)
FORAGEBEEF	.450 (.458)	-.112 (.465)	1.266*** (.380)	-.364 (.360)	-.234 (.356)
NURSERYGH	-.940** (.432)	.007 (.505)	-.293 (.372)	1.608*** (.431)	.410 (.386)
PERENNIALFRT	.455 (.452)	.152 (.562)	.613 (.408)	.009 (.436)	1.201*** (.439)

*** p ≤ .01;** p ≤ .05; * p ≤ .10

Table 5.2. Discrete effects from the probability that an extensionist indicates a particular type of farmer is likely to be able to use climate forecasts to be more successful

Number of Obs = 200

Model	Variable	$\hat{P}^{k}_{S_{r,f}}$	$\hat{P}^{\sim k}_{S_{r,f}}$	$\hat{P}^{k}_{S_{r,f}} - \hat{P}^{\sim k}_{S_{r,f}}$
Row Crop Farmers	FIELDCROP	.918	.636	.283
	NURSERYGH	.672	.816	-.144
Vegetable Farmers	VEGCROP	.911	.801	.110
Livestock Managers	VEGCROP	.426	.691	-.265
	FORAGEBEEF	.749	.487	.262
Nursery Operators	VEGCROP	.496	.672	-.176
	NURSERYGH	.803	.489	.314
Orchard Growers	PERENNIALFRT	.794	.553	.240

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