Farmer adoption and intensity of use of extreme weather adaptation and mitigation strategies: evidence from a sample of Missouri farmers

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Abstract
Climate change and its associated weather extremes pose a threat to agriculture. To slow down climate change and reduce its associated risks, governments around the world are currently developing policies to encourage farmers to engage in adaptation and mitigation efforts. The aim of this study is to assess the adoption and intensity of use of extreme weather adaptation and mitigation strategies among a sample of Missouri farmers and to identify the factors that influence adaptation and mitigation behavior. Of particular interest is the influence of the 2019 Missouri River flooding on adaptation and mitigation efforts. An econometric hurdle model that separates the decision on whether to adopt adaptation/mitigation strategies from the decision on how many strategies to employ was used to achieve the study’s purpose. Improving field drainage or soil water retention capacity for potential flooding was found to be by far the most used adaptation. The most used mitigations were increasing use of minimum tillage, managing fertilizer, and planting cover crops. Types of crops grown, farm income, and opinions on extreme weather events were the most important determinants of both adaptation and mitigation decision. Direct experience with the 2019 Missouri River floods is found to only influence adaptation decision. Adaptation and mitigation intensity were found to be strongly influenced by opinions on government support for adaptation and CRP involvement, respectively. Directions for policy and outreach that can promote adaptation and mitigation efforts among farmers are discussed.

Keywords Weather extremes · Adaptation · Mitigation · Flood experience · Missouri · Hurdle model

1 Introduction

Human-induced greenhouse gas (GHG) emissions and the consequent climate change have led to an increased frequency and severity of weather extremes (IPCC 2021). If global warming continues, extreme weather events and its impacts, such as floods and droughts, are expected
to intensify (Robinson 2021). Because agriculture relies on weather and natural resources, it is susceptible to climate change and extreme weather events. Climate variability and weather extremes threaten agriculture globally (IPCC 2022a). Crop failures, yield losses, and soil degradation are examples of the threats climate change and weather extremes pose to agriculture. These threats can undermine the financial wellbeing of rural communities, lead to more volatile global commodity markets, increase food insecurity, and negatively influence nutrition and mortality (Bitterman et al. 2019; IPCC 2022a). These issues, along with agriculture’s ability to play an important role in GHG reduction, highlight the need to balance mitigation initiatives that reduce GHG emissions with adaptation efforts that enable farmers to manage extreme weather risk more effectively and thus enhance the resilience of agricultural production systems (Elahi et al. 2022; Haden et al. 2012; Howden et al. 2007; McCarl 2010).

Kane and Shogren (2000) define mitigation as “a private or public investment in self-protection to reduce the odds that a bad state of nature is realized” (p.82). The same authors note that mitigation implies decreasing GHG emissions or increasing carbon sequestration. Examples of climate change mitigation strategies that can be used by farmers include optimizing fertilizer application delivery, reducing machinery operations, using diverse crop rotations, planting cover and bioenergy crops, reducing crop tillage, and alternating livestock diets to reduce methane production and release (IPCC 2022b). Adaptation, which is considered a form of self-insurance, is a public or private action to decrease the severity of any realized net damages (Kane and Shogren 2000). Examples of adaptation to climate change at the farm-level include purchasing additional crop insurance, diversifying into other forms of production, supplementing farm income through off-farm employment, restructuring cash flow and debt, scaling back operations, and exiting the industry (Mase et al. 2017). Mitigation and adaptation goals and strategies are intertwined through synergies and trade-offs. An example of synergies is conservation agriculture which builds adaptive capacity through improvements in soil quality and crop diversity and at the same time contributes to mitigation of GHG emissions through improved fertilizer management or more efficient use of machinery and fuels (Harvey et al. 2014; Pradhan et al. 2018). A case of trade-offs is tree monocultures or biofuel crops which can enhance carbon stocks but may lead to land use change elsewhere and a net-increase in GHG emissions (Skevas et al. 2014; IPCC 2022b).

Empirical research on farm-level adaptation and mitigation to climate change in US agriculture has mainly focused on farmers’ intention to adopt different adaptation and mitigation strategies, and a limited number of studies assessed actual adoption of adaptation strategies only (e.g., Bitterman et al. 2019; Linder & Campbell-Arvai 2021; Mase et al. 2017; Running et al. 2019). This literature demonstrates how crop choices, finances, risk perceptions, attitudes about adaptation practices, and belief in climate change affect adaptation behavior (Bitterman et al. 2019; Gardezi and Arbuckle 2020; Lane et al. 2018; Mase et al. 2017; Niles et al. 2016; Roesch-McNally 2018; Running et al. 2019; Valliant et al. 2021). More research documenting the use and intensity of use of different types of adaptation and mitigation strategies in US agriculture and the factors that condition them could help guide the development and implementation of policies to enhance adaptation and mitigation efforts. This in turn could increase the resilience of US agricultural production systems in the face of future climate impacts.

While there is little research tracking actual farm-level adaptation and mitigation to climate extremes in the USA, much research has been done in other parts of the world. The literature tracking actual implementation of adaptation strategies is more abundant than the one on mitigation strategies. Most of the former research has mainly focused on Africa (e.g., Antwi-Agyei et al. 2018; Belay et al. 2017; Bryan et al. 2009; Deressa et al. 2009; Di Falco et al. 2011; Fosu-Mensah et al. 2012; Silvestri et al. 2012) and Asia (e.g. Abid et al.
A handful of adaptation studies also analyzed farmers’ adaptation intensity and its determinants (Diencere 2019; Roco et al. 2014; Thinda et al. 2020). This research identifies the major adaptation strategies implemented by farmers and the factors affecting farmers’ adaptation decisions and intensity. One clear message from this research is that adaptation strategies vary locally depending on agro-climatic and socioeconomic conditions.

Like the adaptation literature, the mitigation literature focuses on farmers’ adoption of various mitigation practices and the factors affecting climate change mitigation behavior (Davidson et al. 2019; Kreft et al. 2021, 2020; Moerkerken et al. 2020; Niles et al. 2016; Rochecouste et al. 2015). Interestingly, some studies have found that mitigation is motivated mostly by the pursuit of economic benefits rather than the desire to reduce GHG emissions (Davidson et al. 2019; Rochecouste et al. 2015). The few US studies on farm-level climate change mitigation, focus either on intended adoption of mitigation strategies (Arbuckle et al. 2013; Haden et al. 2012) or the use of a single mitigation option (i.e., nitrogen fertilizer use reduction) (Schewe and Stuart 2017; Stuart and Schewe 2016). No study in the USA or other parts of the world has investigated the intensity of climate change mitigation efforts undertaken by farmers.

Against this background, the objective of this study is to examine the adoption and intensity of use of climate change adaptation and mitigation strategies by farmers and the factors that help explain adaptation and mitigation behavior. The empirical application focuses on a sample of almost 700 Missouri farmers operating near the Missouri River. The study further investigates the role that personal experience with extreme weather may have in implementing climate change adaptation and mitigation strategies, using the 2019 Missouri River flooding as an example of extreme weather risk experience. The 2019 Missouri River flooding which was caused by above-normal snowpack, saturated soil conditions, deeply frozen soils, and above-average precipitation (NOAA 2019), resulted in 1.2 million acres of prevented planting of corn and soybeans in Missouri (USDA-FSA 2022). The USDA Risk Management Acreage paid over $400 M in indemnities for flood and excess moisture related claims on Missouri corn and soybeans (USDA-RMA 2022). As a result, the Missouri case makes a good candidate for investigating whether extreme weather events influence farmers’ climate change adaptation and mitigation behavior.

This study makes three contributions to the literature. First, it is the first study to assess farm-level climate change adaptation and mitigation intensity in US agriculture (and the rest of the world, for mitigation intensity). Second, it adds to previous work on farm-level climate change adaptation by assessing the factors that influence the adoption and intensity of use of adaptation and mitigation strategies in a US setting. Third, it contributes to previous research on the role of weather extremes on farmer adaptation behavior (e.g., Thinda et al. 2020) by examining the effect of the 2019 Missouri River floods on adoption and intensity of use of climate change adaptation and mitigation strategies.

The rest of the article is organized as follows: “Sect. 2” contains a description of the data and the empirical methods used; “Sect. 3” presents and discusses the empirical results; “Sect. 4” concludes by summarizing key findings and providing insights for successful programs to assist farm-level climate change adaptation and mitigation.

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1 The role of extreme weather events in influencing adaptation attitudes and behaviors has been acknowledged in literature as an important research direction (Mase et al. 2017).
2 Data and empirical methods

2.1 Farmer sampling and survey methods

Data for this study come from a 2022 mail survey of Missouri farmers operating near the Missouri River. In the absence of lists of farmers from which a sample could be drawn, we use an area frame sample built from GIS databases of cropland and grassland (NLCD 2021). The area frame sampling followed a three-step procedure. First, 11 Missouri counties were randomly selected from those counties that border the Missouri River. The metropolitan counties of St. Louis, St. Charles, Jackson, and Clay were excluded from this study. Figure 1 shows the randomly selected counties. In the second step and given that one of the main objectives of this study was to understand how experience with the 2019 Missouri River floods affects extreme weather adaptation and mitigation behavior, the county-specific area from which a sample of landowners would be selected was defined as the area within a 10-mile (16 km) straight line from the Missouri River. This cut-off was selected after consulting agricultural extension experts at University of Missouri. The view of these experts was that the consequences of levee failure on farming and physical infrastructure can reach beyond the flood zone. Next, a stratification

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Fig. 1 The study area

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2 Experts noted that farmers who farm river bottoms have land in the “upland” where they may have their house and shop and maybe animals. Farmers within 10 miles of the river are likely to be affected by the flood. Damage to transportation networks and waterlogged fields that do not drain are some examples of such effects.
occurred within the sample counties by dividing the study area into two strata—flood zone and no flood zone. Data on flood zones came from the Federal Emergency Management Agency (FEMA 2021) and the Soil Survey Geographic Database (SSURGO 2021). The goal was to assure that responses represented (a) farmers who farm in the flood plain of the Missouri River and (b) farmers who do not farm in the flood plain but could be affected by flooding. The final step of the sampling process involved drawing 100 parcels at random from each stratum in each county. This resulted in a balanced final sample frame with 2200 landowners. The identification of selected landowners relied on property tax records obtained from county assessor offices.

The survey was conducted following Dillman et al.’s (2014) total design method. Four mailings were sent out during 2022 as follows: (1) pre-survey postcard to alert recipients (February 7), (2) first questionnaire mailing (February 15), (3) reminder postcard (February 28), and (4) second questionnaire mailing to nonrespondents from the first round (March 14). Of the 2200 questionnaires mailed, 108 were returned as undeliverable, thus leaving 2092 landowners as potential respondents. A total of 835 farmers returned the questionnaire, for a total response rate of 40%. Of these responses, 136 were unusable either because they were incomplete or because the respondents did not meet the basic eligibility criteria. This resulted in a total of 699 usable responses, corresponding to an adjusted response rate of 33%.

2.2 Survey design

The questionnaire on extreme weather adaptation and mitigation behavior was part of a larger survey instrument which also addressed farmer experience and impacts of the 2019 Missouri River flooding and willingness to pay for flood mitigation. In this section, only the parts of the survey relevant to the research questions of the present paper are discussed. These are the following: (a) use of extreme weather adaptation and mitigation strategies, (b) opinions on extreme weather events, (c) current land use, and (d) socioeconomic characteristics.

The section on extreme weather adaptation strategies asked respondents to signal from a list of adaptation strategies those they were already using on their operations. Adoption of extreme weather mitigation strategies was assessed in a similar manner with respondents selecting from a list of GHG reduction strategies those they had already implemented on their farms. Opinions on extreme weather events were elicited using a series of statements to which respondents were asked to rate their level of agreement on a scale of 1 (strongly disagree) to 5 (strongly agree).

In the land use section, respondents were asked how many acres of land they own and/or rent. They were further asked whether they raised livestock on their farmland, what crops they grew, and whether they participated in the Conservation Reserve Program (CRP). Finally, respondents were asked about their socioeconomic characteristics, including age, gender, cooperative membership, farm income, education, farm experience, availability of successor, and experience with the 2019 floods. Table 1 provides descriptive statistics of the socioeconomic and land use characteristics of the sample farms.

3 Where available, the 2021 FEMA Flood Hazard layer was utilized to determine flood plain designation. Unfortunately, this information was not available for Atchison, Holt, and Buchanan counties. In those counties, the NRCS Soil Survey was utilized to determine flood plain designation. In these counties, any soil with a flood frequency rating was designated as flood plain.
2.3 Empirical methods

Our empirical analysis involves two parts. First, descriptive statistics and graphical illustrations are used to assess sample farmers’ a) use of extreme weather adaptation and mitigation practices, and b) perceptions of extreme weather events. In the second part, a two-part hurdle model is used to explore the factors influencing the adoption and intensity of adoption of extreme weather adaptation and mitigation strategies. This model is explained in more detail in the subsection below.

2.3.1 Model estimation for extreme weather adaptation and mitigation

Following Roco et al. (2014) and Thinda et al. (2020), a modeling approach based on a two-step decision process is tested. The first step involves the decision whether to adopt adaptation or mitigation strategies. The second step applies only if the decision to adopt adaptation or mitigation strategies is made and involves the number of strategies adopted. This two-step process was modeled using an econometric hurdle model (Cragg 1971). The hurdle model involves the joint estimation of two equations. The first is a binary probability model that captures the adaptation or mitigation decision (first hurdle). If the first hurdle is passed, a truncated count distribution model is estimated (second hurdle) (Greene 2008; Cameron and Trivedi 2010). In this study, the binary probability model is a logit model, while the truncated count distribution model is a zero-truncated count model.

### Table 1: Descriptive statistics of surveyed farmers (n = 699)

| Variable name       | Definition                                      | Unit     | Mean   | SD    |
|---------------------|-------------------------------------------------|----------|--------|-------|
| Current land use    |                                                 |          |        |       |
| oper_acres          | Operated acres                                  | acres/100| 9.826  | 23.38 |
| rent_out            | Rented out land in 2021                         | (0/1)    | 0.365  | 0.482 |
| rent_in             | Rented in land in 2021                          | (0/1)    | 0.501  | 0.500 |
| grew_corn_soy       | Farmer has grown corn and/or soy                | (0/1)    | 0.857  | 0.351 |
| livestock           | Raised livestock on farm in 2021                | (0/1)    | 0.458  | 0.499 |
| CRP                 | Farmer had land in CRP                          | (0/1)    | 0.295  | 0.456 |
| Background information |                                               |          |        |       |
| Age                 | Age                                             | 1–8a     | 5.715  | 1.243 |
| Male                | Male gender                                     | (0/1)    | 0.860  | 0.348 |
| Coop                | Farmer is a member of a cooperative             | (0/1)    | 0.554  | 0.497 |
| Income              | Gross cash farm income in 2021                  | 1–6b     | 2.655  | 1.991 |
| Education           | Education                                       | 1–6c     | 3.340  | 1.369 |
| Experience          | Farm experience                                 | years    | 38.10  | 18.01 |
| Successor           | Availability of successor                       | (0/1)    | 0.546  | 0.498 |
| Flood               | Farm land/buildings were flooded in 2019        | (0/1)    | 0.610  | 0.488 |

*aAge scaled from 1 (18–24) to 8 (85 and over)*

*bGross cash farm income scaled from 1 (less than $100,000) to 6 ($500,000 and above) and includes income from commodity receipts, farm-related income, and government payments*

*cEducation scaled from 1 (less than 12 years) to 6 (graduate degree)*
Following Tambo and Abdoulaye (2012) and Roco et al. (2014), the combined model can be written as follows:

\[ \alpha^*_i = w_i' \gamma + \epsilon_i \]
\[ \alpha_i = 1 \text{ if } \alpha^*_i > 0 \text{ and } 0 \text{ if } \alpha^*_i \leq 0 \]  
First hurdle (Yes/No decision) \hspace{1cm} (1)

where \( \alpha^*_i \) is a latent variable that describes the decision to employ adaptation/mitigation strategies and \( \alpha_i \) is the observed adaptation/mitigation decision and takes the value of unity if the respondent adapts at least one adaptation/mitigation strategy; \( y^*_i \) is a latent variable related to the intensity of adaptation/mitigation and \( y_i \) is the observed intensity of adaptation/mitigation quantified as the number of adopted adaptation/mitigation strategies; \( w \) and \( x \) are vectors of explanatory variables for adoption decision and intensity, respectively; \( \gamma \) and \( \beta \) are vectors of parameters to be estimated; finally, \( \epsilon_i \) and \( u_i \) are error terms which are assumed to be normally distributed with zero means and constant variances. Given that the parameters \( \gamma \) and \( \beta \) do not have a direct interpretation, it is common to estimate the marginal effects at the mean of each variable (Greene 2008).

To test if the adoption/intensity is a one or a two-step decision, a test procedure used by Roco et al. (2014) was employed. This test involves the use of a likelihood ratio (LR) test to determine if the hurdle model is preferred to a one-step count model (Poisson or negative binomial). The null hypothesis is that the count model outperforms the hurdle model. The LR test involves estimating the logit model, the truncated count model, and the count model with the same variables \( x \) and computing:

\[ \lambda = -2(L_C - L_L - L_{TC}) \]

where \( \lambda \) is the LR statistic and is distributed as chi-square with \( r \) degrees of freedom (\( r \) equals the number of independent variables including a constant); \( L_C \), \( L_L \), and \( L_{TC} \) are the log likelihood function values for the count, logit, and truncated count models, respectively. The count model will be rejected in favor of the hurdle model if the LR statistic value \( \lambda \) exceeds the appropriate chi-square critical value.

If the hurdle model is preferred to the count model, valid statistical inference requires the assumption that the error terms in eqs. (1) and (2) are uncorrelated conditional on all explanatory variables. If this assumption does not hold, coefficient estimates from separate regressions will be biased. To test for conditionally uncorrelated errors between the two regressions above, a method similar to the Heckman test for selection bias (Wooldridge 2010, p.699) is followed, as in Burke et al. (2015). First, the first-stage logit model is estimated and an inverse Mills ratio (IMR) around the probability of adopting adaptation/mitigation strategies is predicted. Second, the second stage zero-truncated count model that assumes conditionally uncorrelated errors and includes IMR as an explanatory variable is estimated. Though not technically necessary for identification, it is common to impose at least one justifiable exclusion restriction when estimating the second stage regression. The null hypothesis \( (H_0) \) of the test described above is that the first and second stage errors are conditionally uncorrelated, and it is tested using the
standard \( t \)-statistic for the coefficient estimate on IMR. If this coefficient is statistically significantly different than zero, then \( H_0 \) is rejected and the model must be re-estimated to conduct valid inference (for more details, see Luca and Perotti (2011)). If \( H_0 \) is not rejected, the second stage parameters are re-estimated excluding IMR.

The explanatory variables included in the specification of the hurdle models and its descriptive statistics are presented in Table 1. These variables were chosen based on the related literature (Roco et al. 2014; Thinda et al. 2020; Diencere 2019) and the particular interests of this study. Researchers have identified factors that affect adaption of climate change adaptation strategies by farmers, including producer and farm characteristics, and perceptions on weather and climate change. Regarding producer characteristics, past studies have found that older farmers are less likely to use climate change adaptation strategies (Roco et al. 2014; Thinda et al. 2020). Hence, we expect a similar effect of the age variable on farmer adaptation/mitigation behavior. Education has been shown in past studies to influence adaptation intensity (Thinda et al. 2020). Other studies, however, find no effect of education on adaptation behavior (Roco et al. 2014; Diencere 2019). Therefore, the effect of education on adaptation/mitigation behavior is ambiguous. Cooperative membership has been shown in past studies to positively affect adaptation (Roco et al. 2014; Diencere 2019). Thus, a variable reflecting cooperative membership is included in the hurdle model regressions and is expected to have a positive sign. Other producer characteristics included in the hurdle model include farm income, farm experience, and availability of successor. Greater farm income can reduce the subjective cost of innovation and the related risks (Rogers 2010), thus leading to higher adaptation/mitigation levels. More farming experience may reduce risk perceptions of new technologies or practices (Feder and Umali 1993), and as a result is expected to positively influence adaptation/mitigation decisions. The presence of a successor may motivate producers to adopt adaptation/mitigation strategies so that the successor can take over a farm that is more resilient to weather extremes. Therefore, availability of successor is expected to have a positive impact on adaptation/mitigation behavior.

Regarding farm characteristics, the literature on the effect of farm size on adaptation is mixed with some studies reporting a positive association (Thinda et al. 2020) and others no association (Diencere 2019). Therefore, the effect of farm size on adaptation/mitigation behavior is an empirical question. Additional land use variables used in the hurdle model include renting in or out land, corn/soybean growers, livestock production, and CRP involvement. The effect of renting in land from other farmers on adaptation/mitigation behavior is ambiguous. On the one hand, renting in land may force producers to create an operation that is more resilient to weather extremes in order to be able to pay the rentals. On the other hand, investments in adaptation practices such as improving field drainage or soil water retention capacity may not be carried out on land that is not owned. Renting out land to other farmers is expected to negatively influence adaptation/mitigation efforts. Renting out land may signal that the farmer is less likely to grow or intensify his/her farming operation (Skevas and Kalaitzandonakes 2020) and thus less interested in employing adaptation/mitigation strategies. There is not much information in the literature on the effect of growing corn or soybeans and raising livestock on weather extreme adaptation/mitigation efforts. Regarding crops grown, Lane et al. (2018) find that New York and Pennsylvania grape and fruit tree growers felt they had fewer options to adapt to climate change than growers of annual crops. Thus, we expect growing corn or soybean to be positively related to adaptation/mitigation. The effect of raising livestock on

\[\text{footnote} \text{ Earlier models controlled for different crop type dummies (e.g., wheat, hay or pasture, tree crops), but these variables were statistically insignificant and dropped from final models.}\]
adaptation/mitigation behavior is an empirical question. CRP involvement is expected to increase adaptation/mitigation efforts. Having land under CRP could reflect environmental conscious behavior, and given that climate change adaptation and especially mitigation practices (such as cover crops) provide additional environmental benefits (e.g., soil and water quality improvement) (Geldenhuys et al. 2021), it could have a positive effect on adaptation/mitigation efforts. In addition to farm and farmer characteristics, opinions on weather extremes were further included in the regressions, with their effect being an empirical question.

Finally, a flood dummy is included in the regressions to test the hypothesis that farmers who were affected by the 2019 Missouri River floods differ in their extreme weather adaptation/mitigation behavior compared with farmers who had no first-hand experience with floods. It was hypothesized that flood experience positively influences adaptation/mitigation behavior. It was further hypothesized that producers without flood experience underestimate the negative affect caused by such an adverse event, thus leading to reduced adaptation/mitigation efforts.

### 3 Empirical results

#### 3.1 Use of extreme weather adaptation and mitigation strategies

Figure 2 shows the type of adjustments undertaken by sample farmers in response to past, present, and expected extreme weather events. About 34% of the survey respondents made no adjustments to their operation. Improving field drainage or soil water retention capacity for potential flooding was the adaptation strategy adopted the most by sample farmers (44%). Adoption of precision agriculture practices was the second

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5 To avoid multicollinearity, not all dummy variables related to opinions on weather extremes were included in the regressions. Furthermore, a backward elimination procedure (P<0.1 to remain) was used to determine which opinion variables to include in the final models.
most used extreme weather adaptation strategy corresponding to 18%, and adjustment of growing practices and or growing new crop varieties the third (16%). The rest of the adaptation strategies shown in Fig. 2 were adopted by 15% or less of the sample.

The intensity of adoption of adaptation strategies by sample farmers is shown in Fig. 3. Survey respondents had adopted on average 1.4 extreme event adaptation strategies. When considering adopters only, 2.2 adaptation strategies were adopted on average.

Concerning adoption of extreme weather mitigation strategies (reflected by use of farm-level practices to decrease GHG emissions), Figs. 4 and 5 show the types and intensity of use of mitigation strategies, respectively. The type of GHG reducing strategy mostly used by sample farmers is increasing use of minimum tillage at
about 52% (Fig. 4). Slightly fewer respondents were managing fertilizer (i.e., right source, rate, time, and place) as a strategy to reduce GHG emissions. The third most important GHG reducing strategy employed by sample farmers was planting cover crops (at 37%). Twenty percent of the sample farmers were reducing energy. The rest of GHG mitigation strategies shown in Fig. 4 were used by less than 5% of the sample. Finally, about 28% of the survey respondents reported not using GHG-reducing strategies.

Regarding the intensity of use of GHG reducing strategies, Fig. 5 shows that survey respondents had been using 1.7 GHG-reducing strategies, on average. When considering adopters only, this figure increases to an average of 2.3 strategies.

It is important to note that in open-ended responses many respondents mentioned that they used the proposed mitigation strategies for common sense business purposes and not for reducing GHG emissions. This finding agrees with the results of previous studies (Rochecouste et al. 2015; Davidson et al. 2019), showing that farmer expectations for economic benefits (rather than GHG reductions) drive the adoption of climate change mitigation practices.

3.2 Opinions on extreme weather events

Regarding opinions on extreme weather, more than half of survey respondents (52%) have noticed more variable or unusual weather on their farms in the past 20 years (Fig. 6). However, only a relatively small proportion of sample farmers (27%) reported that their operation was negatively affected by changes in weather patterns. A higher proportion of respondents (61%) think it is important for farmers to adapt to extreme weather events to ensure the long-term success of US agriculture. Regarding government intervention to mitigate the effects of weather extremes on agriculture, a considerable proportion of respondents (43%) believe the US government should provide technical and financial assistance to farmers to adapt to extreme weather events.
3.3 Decision and intensity of adaptation

Before discussing the estimation results, the steps undertaken to establish the suitability of the selected modeling approach are discussed. The first step was to determine the distribution of probabilities that describe adaptation in the sample data. It was found that the over-dispersion parameter alpha ($\alpha$) (bottom of column 8 in Table 2) is positive (0.244) and statistically significant, implying the negative binomial distribution was more appropriate than the Poisson distribution (Greene 2008) for the outcome of extreme weather adaptation strategies used by sample farmers. The second step was to compare the count data model with the hurdle model by employing the LR test already described in “Sect. 2.3.1.” The count model (i.e. negative binomial model) was rejected at the 1% level of significance (test score = 46.4, df = 18, critical value = 34.8) in favor of the zero-truncated negative binomial model included in the hurdle model. This finding implies that the decision to adopt weather extreme adaptation strategies is made separately from the intensity of adoption, justifying the use of the hurdle model. Finally, the third step was to determine whether the first and second stage errors of the two specifications comprising the hurdle model are conditionally uncorrelated. The coefficient estimate for IMR is statistically insignificant at conventional levels (coef. = −0.509, $p$-value = 0.234). Thus, IMR is excluded from the stage two estimation of the hurdle model. Given the above test results, discussion is focused on results from the hurdle model.

Table 2 shows the econometric results comparing the hurdle model and the negative binomial model. The hurdle model outperforms the count negative binomial model in terms of overall model performance, as shown by the pseudo-$R^2$, which for the hurdle and negative binomial regression is 17.1%, and 5.3%, respectively. The logit model of adoption and the zero-truncated negative binomial model present 8 and 3 out of 17 statistically significant coefficients at least at the 10% level, respectively. For both models, the null hypothesis that the model is statistically insignificant is rejected at the 1% level.

Fig. 6 Sample farmers’ opinions on weather patterns and extremes
Table 2  Estimation of determinants of extreme weather adaptation

| Variables          | Logit (adoption) | Hurdle model | Zero-truncated negative binomial (intensity) | Negative binomial |
|--------------------|------------------|--------------|---------------------------------------------|------------------|
|                    | Coefficient      | Robust standard error | Marginal effect | Coefficient      | Robust standard error | Marginal effect | Coefficient      | Robust standard error | Marginal effect |
| Age                | −0.105           | (0.089)       | −0.019                                      | −0.070           | (0.051)       | −0.114                                      | −0.069*           | (0.039)       | −0.100*                                      |
| Male               | −0.320           | (0.261)       | −0.057                                      | 0.303*           | (0.162)       | 0.442**                                      | 0.068             | (0.119)       | 0.096                                         |
| Coop               | 0.236            | (0.195)       | 0.044                                       | −0.133           | (0.111)       | −0.221                                      | 0.004             | (0.086)       | 0.005                                         |
| Income             | 0.161**          | (0.066)       | 0.030**                                     | 0.049            | (0.032)       | 0.080                                       | 0.066***          | (0.025)       | 0.095***                                      |
| Education          | 0.097            | (0.069)       | 0.018                                       | −0.003           | (0.039)       | −0.006                                      | 0.025             | (0.030)       | 0.037                                         |
| Experience         | −0.002           | (0.006)       | −0.000                                      | 0.006            | (0.004)       | 0.010                                       | 0.003             | (0.003)       | 0.004                                         |
| Successor          | 0.267            | (0.184)       | 0.049                                       | 0.149            | (0.104)       | 0.238                                       | 0.177**           | (0.080)       | 0.252**                                       |
| oper_acres         | −0.007**         | (0.003)       | −0.001**                                    | 0.000            | (0.002)       | 0.001                                       | −0.002            | (0.002)       | −0.003                                        |
| rent_in            | −0.010           | (0.204)       | −0.002                                      | 0.098            | (0.115)       | 0.157                                       | 0.064             | (0.089)       | 0.092                                         |
| rent_out           | 0.161            | (0.194)       | 0.029                                       | 0.068            | (0.109)       | 0.113                                       | 0.078             | (0.084)       | 0.115                                         |
| grew_corn_soy      | 1.110***         | (0.267)       | 0.228***                                    | 0.067            | (0.197)       | 0.107                                       | 0.540***          | (0.143)       | 0.636***                                      |
| Livestock          | 0.461**          | (0.194)       | 0.084**                                     | 0.218**          | (0.102)       | 0.354**                                     | 0.262***          | (0.080)       | 0.380***                                      |
| CRP                | −0.044           | (0.198)       | −0.008                                      | −0.017           | (0.106)       | −0.027                                      | −0.024            | (0.083)       | −0.035                                        |
| Flood              | 0.677***         | (0.195)       | 0.132***                                    | −0.049           | (0.119)       | −0.080                                      | 0.191**           | (0.092)       | 0.266**                                       |
| Hurting            | 0.509**          | (0.252)       | 0.092**                                     | 0.036            | (0.120)       | 0.058                                       | 0.130             | (0.096)       | 0.192                                         |
| Success            | 0.437**          | (0.198)       | 0.080**                                     | 0.058            | (0.106)       | 0.095                                       | 0.154*            | (0.084)       | 0.224*                                        |
| Techsupport        | 0.375*           | (0.198)       | 0.069*                                      | 0.321***         | (0.108)       | 0.523***                                    | 0.297***          | (0.084)       | 0.433***                                      |
| Constant           | −1.282**         | (0.653)       | −0.202                                      | −0.202           | (0.391)       | −0.823***                                    | −0.823***         | (0.289)       | −0.588***                                     |
| Alpha (α)          |                  |               |                                             | 0.244***         |                |                                             | 0.244***          |                |                                              |
| LR χ²              | 96.86***         |               |                                             | 39.69***         |                |                                             | 120.4***          |                |                                              |
Table 2 (continued)

| Variables       | Hurdle model                                           | Negative binomial                                      |
|-----------------|--------------------------------------------------------|--------------------------------------------------------|
|                 | Logit (adoption)                                        | Zero-truncated negative binomial (intensity)           |
|                 | Coefficient    | Robust standard error | Marginal effect | Coefficient    | Robust standard error | Marginal effect |
| Pseudo $R^2$    | 0.142         | 0.0287               |                | 0.0530         |                    |                |
| Log likelihood  | $-381.5$      | $-671.3$             |                | $-1076$        |                    |                |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables “hurting,” “success,” and “techsupport” take the value of 1 for those farmers who agree or strongly agree with the first, fifth, and seventh statement respectively of Fig. 6, and 0 otherwise.
Concerning the socioeconomic determinants of adaptation, being male shows a positive association with the number of adaptation strategies implemented. Net of other variables, being male increases adaptation intensity by 44%, on average. This finding is consistent with those of Diencere (2019), who found male farmers in Benin to be more likely to adopt climate change adaptation practices than female farmers. This result implies that women-led farms may be more vulnerable to extreme weather events than those led by men. As expected, farm income shows a positive and significant effect on the decision to adopt, implying that wealthier farmers are more likely to adapt to extreme weather. This result is in line with those of other studies (Deressa et al. 2009; Silvestri et al. 2012; Roco et al. 2014) showing a positive association between farm income and climate change adaptation in rural communities in Africa and South America. According to Rogers (2010), higher income can reduce the subjective cost of innovation and the associated risks, thus leading to higher adoption rates.

Regarding land use and management characteristics, farm size, as measured by operated acres, has a small negative effect on adoption decision (i.e., the likelihood of adoption decreases by 0.1% for every 100 acres increase in operated cropland), but no effect on adoption intensity. Corn and/or soybean growers were 23% more likely to adopt extreme weather adaptation practices than growers of other crops. This result could be explained by the finding of Lane et al. (2018) that grape and fruit tree growers in New York and Pennsylvania perceived they had fewer options to adapt to climate change than farmers of annual crops.

Raising livestock on farm was found to impact positively the likelihood of both adoption and intensity of adoption of extreme weather adaptation strategies. The flood dummy is another important determinant of adoption decision. The marginal effect of this variable indicates that the probability of adaptation is 13% higher for those farmers whose land and/or farm buildings were affected by the 2019 floods. Thinda et al. (2020) in their study of adoption of climate change adaptation strategies among South African farmers did not find a significant effect of flood experience on the likelihood of adaptation.

In terms of attitudinal factors, the model indicates that farmers who believe that extreme weather events are hurting their farm operations and those who view extreme weather adaptation as a necessary condition for the long-term success of US agriculture are more likely to adopt strategies to cope with weather extremes. Similarly, respondents who agree that the government should provide technical and financial assistance to farmers to adapt to extreme weather events are more likely to use adaptation strategies. These farmers are also more likely to apply a higher number of extreme weather adaptation strategies, with the marginal effect being 52%.

### 3.4 Decision and intensity of mitigation

To establish the suitability of the selected modeling framework, similar tests to those undertaken for the adaptation analysis have also been performed for the mitigation analysis. It was found that the over-dispersion parameter alpha (α) is close to zero and statistically insignificant (see Table 4 in the Appendix), implying the Poisson distribution
Table 3  Estimation of determinants of extreme weather mitigation

| Variables   | Logit (adoption) | Hurdle model | Zero-truncated Poisson (intensity) | Poisson |
|-------------|------------------|--------------|-----------------------------------|---------|
|             | Coefficient      | Robust standard error | Marginal effect | Coefficient | Robust standard error | Marginal effect | Coefficient | Robust standard error | Marginal effect |
| Age         | −0.031           | (0.097)       | −0.005              | −0.077*     | (0.040)       | −0.155*             | −0.063**     | (0.030)     | −0.106**             |
| Male        | 0.162            | (0.272)       | 0.026               | 0.230*      | (0.135)       | 0.424*              | 0.179*       | (0.099)     | 0.284*              |
| Coop        | 0.367*           | (0.206)       | 0.060*              | 0.092       | (0.084)       | 0.182               | 0.149***     | (0.063)     | 0.248***             |
| Income      | 0.253***         | (0.075)       | 0.040***            | 0.062***    | (0.023)       | 0.126***            | 0.083***     | (0.018)     | 0.141***             |
| Education   | 0.136*           | (0.078)       | 0.022*              | 0.043       | (0.029)       | 0.087               | 0.052**      | (0.021)     | 0.088**             |
| Experience  | 0.000            | (0.007)       | 0.000               | 0.008**     | (0.003)       | 0.015**             | 0.005**      | (0.003)     | 0.009**             |
| Successor   | 0.223            | (0.201)       | 0.036               | −0.017      | (0.077)       | −0.034              | 0.027        | (0.061)     | 0.045               |
| oper_acres  | −0.009**         | (0.004)       | −0.001**            | 0.001       | (0.002)       | 0.001               | −0.002       | (0.001)     | −0.003              |
| rent_in     | 0.286            | (0.225)       | 0.046               | −0.083      | (0.087)       | −0.169              | 0.017        | (0.069)     | 0.029               |
| rent_out    | −0.024           | (0.203)       | −0.004              | −0.063      | (0.082)       | −0.125              | −0.036       | (0.062)     | −0.061              |
| grew_corn_  | 1.718***         | (0.273)       | 0.343***            | 0.010       | (0.165)       | 0.020               | 0.716***     | (0.166)     | 0.920***             |
| soy         |                  |               |                     |             |               |                     |             |             |                     |
| Livestock   | 0.427**          | (0.209)       | 0.067**             | 0.062       | (0.074)       | 0.126               | 0.129**      | (0.086)     | 0.220**             |
| CRP         | 0.030            | (0.222)       | 0.005               | 0.206***    | (0.074)       | 0.429***            | 0.143**      | (0.059)     | 0.249**             |
| Flood       | −0.112           | (0.210)       | −0.018              | 0.014       | (0.090)       | 0.029               | 0.002        | (0.067)     | 0.003               |
| Hurting     | 0.256            | (0.248)       | 0.040               | 0.091       | (0.084)       | 0.186               | 0.124**      | (0.062)     | 0.215*              |
| Success     | 0.616***         | (0.216)       | 0.097***            | 0.169**     | (0.078)       | 0.342**             | 0.235***     | (0.059)     | 0.401***             |
| Constant    | −2.232***        | (0.711)       | 0.059               | (0.312)     | −0.898***     | (0.250)             | −8.988***    | (0.250)     | −1072.7              |
| LR $\chi^2$ | 108.9***         |               |                      | 85.30***    |               |                     | 212.8***     |             |                     |
| Pseudo $R^2$ | 0.173            |               |                      | 0.0570      |               |                     | 0.0925       |             |                     |
| Log likelihood | −340.3       |               |                      | −705.3      |               |                     | −1072.7     |             |                     |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Variables “hurting” and “success” take the value of 1 for those farmers who agree or strongly agree with the first, and fifth statement respectively of Fig. 6, and 0 otherwise.
was more appropriate than the negative binomial one (Greene 2008) for the outcome of GHG mitigation strategies applied by sample farmers. Regarding the comparison between the hurdle and count models, the LR test shows that the count model (i.e., Poisson model) is rejected at the 1% level of significance (test score = 54.2, df = 17, critical value = 33.4) in favor of the zero-truncated Poisson model included in the hurdle model. This result validates the hypothesis that the decision to adopt GHG mitigation practices is made separately from the intensity of adoption, which supports the use of the hurdle model. Finally, it was found that the coefficient of IMR is statistically insignificant (coef. = 0.068, p-value = 0.837), meaning that the first and second stage errors of the hurdle model are conditionally uncorrelated. This finding implies that valid inference can be conducted using the hurdle model. As a result, the discussion below focuses on the findings of the hurdle model.

The econometric results comparing the hurdle model and the Poisson model are presented in Table 3. The pseudo-$R^2$ for the hurdle and count Poisson regression is 23%, and 9%, respectively, implying that the hurdle model outperforms the count Poisson model in terms of overall model performance. The logit model of adoption and the zero-truncated Poisson model have 7 and 6 out of 16 statistically significant coefficients at least at the 10% level, respectively. Both models are statistically significant based on their chi-square coefficients.

Regarding the determinants of GHG mitigation, six variables under the category of socioeconomic characteristics had a statistically significant impact on the adoption and/or intensity of adoption of GHG mitigation strategies. These variables were farmer age, gender, cooperative membership, farm income, farmer educational level, and farming experience. Age shows a negative and statistically significant effect on the intensity of adoption only, indicating that younger farmers are more likely to adopt a higher number of mitigation strategies. Roco et al. (2014) and Thinda et al. (2020) report a similar finding but in the context of climate change adaptation of farmers in Chile and South Africa, respectively. Unlike younger farmers, older farmers have a short-time-planning horizon which may discourage them from adopting new practices and technologies (Skevas and Kalaitzandonakes 2020). Being male has a positive influence on intensity of mitigation. Male farmers were more likely to adopt a higher number of GHG mitigation strategies compared to female producers, with the marginal effect being 42.4%.

Cooperative membership increases the likelihood of adoption by 6%. A similar finding is reported by Roco et al. (2014), who found that participation in farmer associations was positively related to adoption intensity of climate change adaptation practices in Chile. Farmers who are members of cooperatives can be expected to be more receptive to innovations because cooperatives expose farmers to new technologies and facilitate knowledge spillovers (Carrer et al. 2017). Farm income has a positive and significant effect on both the decision to adopt and the intensity of adoption of mitigation practices. Greater farm income may allow risk capital to be used for experimentation with new practices.

The coefficient of education is positively signed and statistically significant in the adoption model only. Its marginal effect indicates that more educated farmers were 2.2% more likely to adopt GHG mitigation strategies. Thinda et al. (2020) in their study of adoption of climate change adaptation strategies among smallholder farmers in South Africa found a similar effect of education on the probability of adopting more climate change adaptation strategies. More educated farmers may be more receptive to new farm practices and see the potential importance of reducing GHG emissions.
Farming experience was found to have a positive and significant impact on mitigation intensity. More experienced producers may be more likely to adopt new practices and technologies because they are better able to assess the related costs and benefits.

Regarding land use and management practices, farm size, types of crops grown, livestock production, and CRP involvement influenced the decision to adopt GHG mitigation strategies and/or the mitigation intensity. Farm size, as measured by operated acres, has a negative but relatively small effect on adoption decision. In the context of adoption of climate change adaptation strategies, Thinda et al. (2020) reported a positive effect of farm size on adaptation. Farmers who grew corn and/or soy and those who raised livestock are more likely to apply GHG mitigation practices. Finally, the intensity of mitigation is strongly influenced by CRP participation, which increases the probability of mitigation intensity by 43%.

Moving to the results of the attitudinal variables, farmers who deemed extreme weather adaptation to be important for the success of US agriculture are more likely to adopt and use more GHG mitigation strategies. This finding illustrates the positive influence that more information on the long-term effects of adaptation on farming may have on adoption of GHG mitigation practices.

4 Conclusions and policy implications

Erratic and extreme weather events pose significant risks to agricultural production. Under climate change, the frequency and intensity of weather extremes could increase (IPCC 2018). It is, therefore, important to understand the strategies used by farmers to adapt and mitigate the risks posed by weather extremes, and the factors that determine the decision and intensity of use of such strategies.

This study surveyed almost 700 Missouri farmers to explore their behavioral and attitudinal response to extreme weather risk. Behavioral responses encompassed both adaptive and mitigative strategies, and the decision and intensity of use of such strategies was assessed using a hurdle model that separates the decision on whether to adopt adaptation/mitigation strategies from the decision on how many strategies to employ. Of specific interest was to assess how the 2019 Missouri River flooding affected farmers’ adaptation and mitigation behavior.

The results highlight several aspects that deserve special attention in the formulation of policy interventions to increase adaptation and mitigation efforts. First, a considerable proportion of the surveyed farmers have not applied any adaptation (34%) and mitigation (28%) strategies to cope with extreme weather risk. The analysis of the determinants of adoption decision revealed that non-adopters (of both types of strategies) were mainly lower-income farmers who did not grow corn or soybeans and did not perceive extreme weather adaptation to be important for the long-term success of US agriculture. These results give a picture of producers that could be targeted with information (about the need and benefits of adaptation and mitigation) and financial and technical assistance to adopt extreme weather adaptation and mitigation strategies. However, this insight should be used with caution given that the question of targeting producers is not really addressed in this study. Regarding non-corn/soybean growers (e.g., producers using pasture and hay ground, tree fruit crop farmers), it could be that they have...
fewer adaptation options or require higher cost solutions than corn and soybean farmers, as suggested by some studies (Lane et al. 2018). In that case, financial assistance and/or research efforts to develop and identify cost-effective adaptation practices may enhance adaptation efforts. This implication is in line with the findings from the attitudinal analysis where a considerable number of respondents noted that the US government should provide technical and financial assistance to farmers to adapt to weather extremes. One question that arises from this discussion, however, is whether the government should spend resources to target farmers not yet concerned with climate change and its effects or provide its scarce resources to those already likely to adopt adaptation/mitigation strategies. Another question is whether targeting should be towards farmers most likely to have the greatest impact from a single unit of resources spent on adaptation/mitigation. These questions are not addressed here and are important topics for further research.

Second, direct experience with the 2019 Missouri River flooding motivated sample farmers to show extreme weather adaptation behavior (but did not affect mitigation). It could be that producers who were not affected by flooding underestimate the negative effect associated with floods, and extreme weather events more generally. In that case, risk communication about the negative consequences (both economic and emotional) of weather extremes may trigger motivation for adaptation behavior. Another explanation for the above finding could be that the timing of the survey has affected adaptation rather than mitigation. Farmers affected would have real incentive to put in adaptation (with short-term benefits) and less free cash to put in mitigation (with long-term benefits).

Third, the most important factor exerting a positive influence on mitigation intensity was CRP involvement. The implication is that environmental consciousness or conservation orientation (as reflected in CRP involvement) increases the number of mitigation strategies adopted. This finding together with the observation that many sample farmers viewed the proposed mitigation measures as good business practices imply that outreach that focuses on the economic and environmental benefits of climate-mitigative practices (rather than GHG reductions) could be an effective way to achieve mitigation of climate change. This insight is strengthened by the fact that farmer beliefs about the anthropogenic causes and implications of climate change are often hard to change (Carlton et al. 2016), rendering efforts to alter such beliefs a rather ineffective strategy for promoting mitigation.

The present study was limited in the range of factors that likely impact adoption and intensity of use of adaptation and mitigation strategies to cope with the effects of weather extremes. Variables related to perceived challenges to adaptation/mitigation such as lack of knowledge on adaptation/mitigation measures, high application costs, and time constraints may affect adaptation/mitigation efforts. Another limitation of this study is the use of cross-sectional data. A longitudinal approach would allow an exploration of the ways in which adaptation/mitigation might change within farms across time. It would further allow to fully control for time-invariant unobserved heterogeneity such as personality traits and cultural factors that may affect adaptation/mitigation behavior.
Appendix

Table 4 Results of the negative binomial model for extreme weather mitigation

| Variables          | Coefficient | Robust standard error |
|--------------------|-------------|-----------------------|
| Age                | −0.063***   | (0.032)               |
| Male               | 0.179*      | (0.102)               |
| Coop               | 0.149**     | (0.068)               |
| Income             | 0.083***    | (0.019)               |
| Education          | 0.052**     | (0.023)               |
| Experience         | 0.005**     | (0.002)               |
| Successor          | 0.027       | (0.063)               |
| oper_acres         | −0.002      | (0.001)               |
| rent_in            | 0.017       | (0.070)               |
| rent_out           | −0.036      | (0.067)               |
| grew_corn_soy      | 0.716***    | (0.132)               |
| Livestock          | 0.129**     | (0.062)               |
| CRP                | 0.143**     | (0.063)               |
| Flood              | 0.002       | (0.072)               |
| Hurting            | 0.124*      | (0.070)               |
| Success            | 0.235***    | (0.065)               |
| Constant           | −0.898***   | (0.239)               |
| Alpha (α)          | 5.24e−08    |                       |
| LR $\chi^2$       | 209.5***    |                       |
| Pseudo $R^2$       | 0.0890      |                       |
| Log likelihood     | −1073       |                       |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to confidentiality reasons.

Declarations

Competing interests The authors declare no competing interests.

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